Advanced Automated Recognition: a true Integration of AI and Nature for Multifaceted Image Analysis

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By

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DECLARATION OF ORIGINALITY AND COMPLIANCE OF ACADEMIC ETHICS

I hereby declare that this thesis contains a comprehensive survey on previous works as well as some original technical contribution by the undersign candidate, as part of my Master of Technology in Intelligent Automation and Robotics offered by the department of Electronics and Telecommunication Engineering of Jadavpur university. All information in this document has been obtain and presented in accordance with academic rules and ethical conduct. I also declare that I have thoroughly cited and referenced all material and findings which are not original to this research, as provided by these rules and conduct.

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Conferences:
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Patents
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Title: Advanced Automated Recognition: a true Integration of AI and Nature for Multifaceted Image Analysis

Abstract:

Image classification using deep neural networks is a powerful technique in the field of computer vision, enabling machines to understand and categorize visual data with high accuracy. Deep neural networks, particularly convolutional neural networks (CNNs), have revolutionized image classification tasks due to their ability to automatically learn hierarchical features from raw pixel data. This thesis mainly focuses on automated categorization of diseased and healthy leaf samples, distinct foliage species, estimation of fruits and vegetables freshness as well as automated shoreline detection and curation of new databases for machine printed and handwritten documents classification in Bengali language.

The export of fresh fruits plays a pivotal role in both national and international economies, providing a significant source of income for countless farmers. Ensuring the freshness and edibility of these fruits is crucial for maintaining quality during export and minimizing financial losses. Recent advances in deep neural networks have led to their successful application in non-invasive image classification tasks, including the quality assessment of various plant parts such as leaves, fruits, and vegetables. These methods are not only more time-efficient but also cost-effective. However, a major challenge faced by researchers in developing these automated systems is the scarcity of appropriate databases necessary for training. Addressing this gap, I have developed a new database called “FruityHub”, which includes 1786 image frames of eight different fruit types: Dragon Fruits, Net Melons, Strawberries, Star Fruit, Zucchini, Mango, Pineapple, and Plum. Each fruit category in FruityHub is classified into three conditions: Fresh, Damaged, and Severely Damaged, aiding in the automated assessment of fruit quality based on characteristics like skin colour, texture, and shape. I have also evaluated the effectiveness of this database using fourteen deep neural network models, including AlexNet, Vgg16, ResNet152, MobileNetv2, ShuffleNetv2, SqueezeNet, InceptionV3, InceptionResNetv2, DenseNet121, NasNetLarge, NasNetMobile, GhostNetv2, EfficientNetB7, and Xception. The performance of these models was assessed using metrics such as Test Accuracy, Recall, Precision, and F1 Score.

The burgeoning field of automated leaf classification has made significant strides with the advent of advanced deep neural technologies. My latest research introduces "GreenMedNet," a groundbreaking and computationally efficient deep neural network tailored specifically for the classification of insulin leaves into diseased and healthy categories, given their intrinsic hyperglycemic properties. This study marks a pivotal advancement with the development of the "GreenMedNet" architecture, which ingeniously captures multiscale contextual information while maintaining a streamlined parameter count. A cornerstone of my innovation lies in the creation of a novel activation function that merges the advantages of existing functions in a scalable manner, effectively safeguarding the network against common pitfalls like vanishing gradients and the dying ReLU issue. This enhancement not only preserves the non-linear dynamics essential for

deep learning but also optimizes the selection of hyperparameters to boost the overall efficiency of the network. Supporting my research is the meticulously curated "Nature's Diabetes Helpers: Insulin Leaves Repository." This custom database comprises 600 meticulously balanced images, split evenly between healthy and damaged classes, providing a robust foundation for training, and testing my model. "GreenMedNet" has demonstrated remarkable effectiveness, achieving a Test Accuracy of 99.17%, complemented by high scores in Precision, Recall, and F1 metrics. This impressive performance not only confirms the network's robustness but also highlights its superiority over existing models, establishing "GreenMedNet" as a significant contribution to the field of leaf classification technology.

In the dynamic field of vegetable quality assessment, innovative automated technologies have revolutionized the way I evaluate freshness. These systems, which analyze external morphology, texture, and colour, stand out as both efficient and economical solutions. They play an instrumental role in ensuring that only the finest vegetables reach both local and international markets, thereby substantially enhancing the revenue streams of the global food industry. The significance of this technological advancement has not gone unnoticed in the research community. Enthusiastic about its potential, scientists have been keen to harness advanced deep learning technologies to accurately categorize vegetables into distinct quality classes. However, the success of these cutting-edge methods largely depends on the availability and quality of training and validation databases. This presents a notable challenge, as there is a pressing need for more comprehensive and representative datasets to refine and validate these automated systems effectively.

Optical Character Recognition (OCR) plays a critical role in the digitization of documents, making textual content searchable and editable, thus streamlining workflows, and extracting actionable insights. It not only enhances accessibility for those with visual impairments but also underpins e-government initiatives and optimizes document management systems. OCR technology significantly enriches customer interaction platforms, assists in adhering to financial and legal regulations, and synchronizes seamlessly with advanced technologies such as Computer Vision, Natural Language Processing, and Machine Learning. As a cornerstone technology, OCR transforms analog documents into valuable digital formats, promoting greater operational efficiency, accuracy, and accessibility across various industries in today's digital landscape.

In the realm of OCR applications, the distinction between handwritten and machine-printed texts is critical, necessitating tailored processing techniques for each. Handwritten texts require sophisticated algorithms, often based on neural networks with Long Short-Term Memory (LSTM) layers, to interpret diverse and complex writing styles. Conversely, machine-printed texts can be processed using relatively straightforward algorithms such as template matching due to their uniformity. Adaptive pre-processing strategies are essential, with techniques for handwritten texts focusing on normalizing writing styles and managing cursive scripts, while machine-printed texts may involve binarization and

noise reduction. For feature extraction, handwritten OCR systems analyze characteristics like loops and slant angles, whereas machine-printed OCR systems concentrate on geometric properties. The selection of training data also varies significantly; handwritten text recognition systems benefit from datasets rich in writing style variability, whereas machine-printed systems utilize more standardized font collections. By employing document-type specific processing and adaptive learning techniques, OCR systems can significantly enhance both accuracy and processing efficiency, thereby optimizing the overall performance of OCR technologies.

Automated prediction and assessment of coastline changes using advanced technologies like deep learning networks and machine learning methods are gaining significant attention for their reliability and efficiency. This research area is crucial in today's context, playing a vital role in sustainable coastal development, environmental conservation, disaster risk mitigation, and decision-making impacting both human communities and coastal ecosystems. While automated shoreline change prediction has been proposed by some, it remains relatively underexplored. My study aims to fill this gap by conducting a comprehensive analysis of existing methods, covering various aspects such as data sources and methodological approaches. By delving deeply into this subject, My work seeks to provide valuable insights to researchers and offer solutions to unexplored territories within this domain.

The works presented in this thesis offer several noteworthy contributions, including:

FruityHub: A diverse collection of fruits created for edibility estimation.

GreenMedNet: A computationally inexpensive hyperparameter optimised for efficient classification of healthy and damaged insulin leaves.

Natural vegetable progression evaluation through new developed database (VDBB). Nature's Best vs. Bruised: A Veggie Evaluation

BengaliPrintDB: A Repository of Machine-Printed Bengali Documents

In-depth survey of automated shoreline alteration identification methods

This thesis addresses three critical problems selected for their profound real-world significance. Through detailed analysis of statistical data from reputable sources, the practical importance of each topic is thoroughly explored. Additionally, an extensive literature review is provided for each problem, highlighting deficiencies in existing approaches and proposing novel methods to address these shortcomings.

Chapter 1

1. Introduction

This chapter provides a concise summary of the problem statements investigated in this thesis, offering a detailed examination of their real-world significance backed by statistical data from authoritative sources. It also outlines the fundamental principles of machine learning and deep learning utilized for image processing in this study. Additionally, the chapter concludes with a comprehensive overview of the thesis structure and organization.

1.1 FruityHub: A diverse collection of fruits created for edibility estimation:

The export of fresh fruits significantly impacts both national and global economies while providing vital livelihoods for numerous farmers. Automating the assessment of fruit edibility, crucial for maintaining export quality and reducing financial losses, has become imperative. Leveraging the remarkable performance of deep neural networks in image classification tasks, researchers have developed automated methods to identify the quality of various plant parts in a more efficient and cost-effective manner. However, a major challenge faced by researchers is the lack of comprehensive databases required for training such methods. To address this gap, I have introduce FruityHub, a novel database comprising 1786 image frames spanning eight different types of fruits, including Dragon Fruits, Net Melons, Strawberries, Star Fruit, Zucchini, Mango, Pineapple, and Plum. Each fruit category's image frames are categorized as Fresh, Damaged, or Severely Damaged, enabling automated estimation of fruit quality based on characteristics such as skin colour, texture, and shape. I have validate the efficacy of this database using fourteen deep neural networks, including AlexNet, Vgg16, ResNet152, MobileNetv2, ShuffleNetv2, SqueezeNet, InceptionV3, InceptionResNetv2, DenseNet121, NasNetLarge, NasNetMobile, GhostNetv2, EfficientNetB7, and Xception, assessing their performance through metrics like Test Accuracy, Recall, Precision, and F1 score.

1.1.1. TABLE I. EXISTING FRUIT DATABASES:

Database	Contents	Classes	Application Area
Citrus Plant Database	Citrus Fruits	Black spot	Fruit and Leaf disease detection
		Canker	
		Greening	
		Healthy	
		Scab (Fruit)/Melanose (Leaves)	
Guava Dataset	Guava Leaves and Fruits	Disease Free	Guava Fruit and Leaf disease detection
		Phytopthora	
		Red rust	
		Scab	
		Styler and Root	
PSFD-Musa Dataset	Banana Deficiency	Potassium Deficiency	Banana fruit disease, variety and deficiency detection
	Banana Disease	Resized Bacterial Soft Rot	
		Resized Banana Aphids	
		Resized Banana Fruit-Scarring Beetle	
		Resized Black Sigatoka	
		Resized Panama Disease	
		Resized Pseudostem Weevil	
		Resized Yellow Sigatoka	
	Banana Variety	Resized Bhimkol	
		Resized Jahaji Fruit	
		Resized Jahaji Leaf	
		Resized Jahaji Stem	
		Resized Kachkol Fruit	
		Resized Malbhog Fruit	
		Resized Malbhog Leaf	
FruitNet: Indian Fruits Dataset with Quality	Bad Quality_Fruits/ Good Quality_Fruits/ Mixed Quality_Fruits	Apple_Bad/ Apple_Good/ Apple	Fruit quality detection
		Banana_Bad/ Banana_Good/ Banana	
		Guava_Bad/ Guava_Good/ Guava	
		Lime_Bad/ Lime_Good/ Lemon	
		Orange_Bad/ Orange_Good/ Orange	
		Pomegranate_Bad/ Pomegranate_Good/ Pomegranate	
FruitsGB: Top Indian Fruits with quality	Apple	Bad Apple/ Good Apple	Fruit quality detection
	Banana	Bad Banana/ Good Banana	
	Lime	Bad Lime/ Good Lime	
	Orange	Bad Orange/ Good Orange	
	Pomegranate	Bad Pomegranate/ Good Pomegranate	

1.1.2. Significance of the database in real world:

In 2016, a research article [1] emphasized the substantial impact of pest and mite attacks, coupled with diseases caused by bacteria, fungi, and viruses, on crop yields in India. The study reported an annual loss of approximately 15-25% in crop yield due to these factors. Additionally, another publication [2] underscored the severe economic consequences, revealing a staggering financial loss of Rs 50,000 crore each year attributed to crop damage in India.

A recent global survey led by Prof. Maria Lodovica and ten other scientists from the University of Turin, Italy, unveiled that pest attacks lead to a significant annual wastage of approximately 40% of the global crop yield. This revelation, shared during the 2021 launch of the UN Food and Agriculture Organization's convention, highlighted a staggering financial loss of 70 billion dollars worldwide due to this crop wastage. Moreover, the survey also estimated an additional annual financial loss of 220 billion dollars attributed to various plant diseases. These findings underscore the urgent need for concerted efforts to address and mitigate the impact of pests and plant diseases on global agriculture and food security.

In the fiscal year 2022-23, India experienced notable success in the export of fresh fruits and vegetables, amounting to Rs. 13,185.30 crores, as reported in [3]. This export figure was divided into two categories: Fresh Fruits, contributing Rs. 6,219.46 crores, and vegetables, adding Rs. 6,965.83 crores to the overall export value. The substantial export of these perishable commodities not only signifies a substantial financial contribution but also highlights India's significant role in international agricultural trade, showcasing its market presence and competitiveness in the global arena.

In the fiscal year 2023, India witnessed substantial success in fresh fruit exports, reaching nearly 863.7 million U.S. dollars, as reported by A. Minhas in a June 6, 2023 publication [4]. The export value of processed fruits and juices during the same period surpassed 908 million U.S. dollars, showcasing a consistent upward trend since fiscal year 2020. This growth reflects a positive trajectory in the processed fruit sector, indicating increasing international demand and popularity for Indian fruit products.

Despite the economic significance of fruit exports, a notable concern arises from potential damage caused by viruses, fungi, bacteria, or pest attacks. Therefore, there is a pressing need for automated systems to evaluate the edibility of these fruits, ensuring the quality of exported products. Such technological advancements are crucial to maintaining and enhancing the reputation of Indian fruits in the global market by addressing and mitigating quality-related challenges.

1.2. GreenMedNet: A computationally inexpensive hyperparameter optimised dual attention based insulin leaves categorization approach:

The realm of plant pathology has witnessed a transformative shift with the advent of advanced deep learning technologies, particularly in the automated classification of leaf categories. My study introduces a pioneering deep neural network, dubbed "GreenMedNet," engineered to deftly classify insulin leaves into diseased and healthy categories based on their inherent hyperglycemic attributes. The innovation of GreenMedNet lies in its architecture, which ingeniously leverages multiscale contextual information, achieving high computational efficiency while maintaining a minimal parameter footprint. A distinctive feature of my work is the development of a novel activation function crafted by amalgamating the advantages of established functions into a scalable format. This innovation is designed to enhance the preservation of non-linearities within the network, effectively mitigating common issues such as vanishing gradients and the dying ReLU problem. Further, meticulous hyperparameter tuning was employed to optimize network performance, ensuring robustness and efficiency. To facilitate my research, I have curated an exclusive dataset titled "Nature's Diabetes Helpers: Insulin Leaves Repository." This custom database, meticulously balanced, comprises 600 images split evenly between healthy and damaged classes (300 images each). The diversity of this dataset makes it an invaluable asset for training deep learning models in the context of plant health. The capabilities of GreenMedNet have been rigorously tested, yielding an impressive Test Accuracy of 99.47%, alongside stellar Precision, Recall, and F1 scores. These results not only validate the effectiveness of my network but also underscore its superiority in comparison to existing models, marking a significant advancement in the field of computational botany and deep learning applications in agriculture.

1.2.1. Significance of the problem statement in real world:

Annually, agricultural sectors in India and worldwide confront significant economic adversity due to crop yield deficits arising from pervasive plant diseases. These afflictions are primarily induced by pathogens such as bacteria, viruses, fungi, and pests, as well as the misapplication of excessive pesticides. [5] A 2016 study indicated that India experiences an estimated annual crop yield diminution of 15-25% due to diseases stemming from pest and mite invasions, along with bacterial, fungal, and viral infestations. Concurrently, a report [6] underscored that these crop damages precipitate an annual economic loss amounting to approximately Rs 50,000 crore.

In a related survey conducted by Prof. Maria Lodovica and a team of ten researchers at the University of Turin, Italy [7], it was revealed that pests obliterate about 40% of global annual crop yields. This significant loss was highlighted by the Director-General of the UN Food and Agriculture Organization during their 2021 convention, marking a global financial setback of around 70 billion dollars. When aggregated, the economic impact of various plant diseases totals an astounding 220 billion dollars annually.

To tackle this global challenge with both cost efficiency and expediency, researchers have pioneered various deep neural network architectures specifically tailored for the identification of leaf diseases. These innovations leverage the recent triumphs of deep neural networks in intricate image classification and detection tasks. Crucially, the efficacy of these technologies hinges on the meticulous selection of training databases, which play a pivotal role in fine-tuning the performance of these sophisticated neural architectures, ensuring their precision and reliability in real-world applications.

1.3 Natural vegetable progression evaluation through new developed database (VDBB). Nature's Best vs. Bruised: A Veggie Evaluation

In the realm of evaluating vegetable freshness, automated methods that analyze external morphology, texture, and colour have emerged as efficient and cost-effective tools. These methods play a crucial role in sorting high-quality vegetables for both export and local consumption, significantly impacting the revenue of the food industry worldwide. Recognizing the importance of this area, researchers have developed various automated techniques, often leveraging advanced deep learning technologies to categorize vegetables into specific classes. However, the effectiveness of these methods heavily depends on the quality of the databases used for training and validation, posing a challenge due to the lack of suitable datasets.

1.3.1 Significance of the problem statement in real world:

My research introduces a novel database named "Vegetable Database: Best vs. Bruised (VDBB)," comprising 4464 images representing six commonly consumed vegetables in India: Cowpea (Vigna sinensis Savi), Snake Gourd (Trichosanthes cucumerina), Spiny Gourd (Momordica dioica), Ivy Gourd (Coccinia grandis), Taro root (Colocasia esculenta), and Turmeric (Curcuma longa). These vegetables were chosen for their affordability and widespread consumption in India, particularly in rural areas, and were notably absent in existing databases. The images in my database depict the natural progression of these vegetables from a fresh state to damaged and severely damaged conditions without any external manipulation. I have defined three classes: Fresh, Damaged, and Severely Damaged, and captured the images against a white background, using diverse camera angles and artificial lighting conditions. This comprehensive database serves as a valuable resource for researchers in the field, addressing the critical need for robust datasets and facilitating advancements in automated vegetable quality assessment techniques.

1.4 BengaliPrintDB: A Repository of Machine-Printed Bengali Documents

Distinguishing between handwritten and machine-printed documents holds paramount importance in OCR applications due to their distinct processing requirements. Handwritten text necessitates specialized recognition algorithms, such as neural networks with LSTM layers, to address the complexities of various writing styles. Conversely, machine-printed text benefits from simpler algorithms like template matching. Adaptive pre-processing techniques play a crucial role, involving style normalization and cursive writing handling for handwritten documents, while machine-printed documents focus on tasks like binarization and noise reduction. Feature extraction techniques differ as well, with handwritten text focusing on capturing loops and slant, whereas machine-printed text emphasizes geometric properties. Training data selection also varies, with diverse datasets for handwritten OCR models and uniform fonts for machine-printed OCR models. Efficiency is further enhanced through selective processing based on document type, and adaptive learning strategies contribute to overall OCR performance improvement. In summary, tailoring techniques to differentiate between these document types is essential for optimizing OCR accuracy and efficiency.

1.4.1 Real-life significance of the problem statement:

In the contemporary era, Optical Character Recognition (OCR) stands as a vital tool for digitizing documents, thereby enhancing searchability, automating workflows, and extracting valuable insights from textual data. Its significance extends to improving accessibility for the visually impaired, supporting e-government services, and ensuring efficient document management. Furthermore, OCR contributes to enriched customer experiences, aids in financial and legal compliance, and seamlessly integrates with technologies like Computer Vision, Natural Language Processing, and Machine Learning for advanced capabilities. By transforming physical documents into actionable digital data, OCR plays a foundational role in fostering efficiency, accuracy, and accessibility across various sectors in the digital age. Recognizing the importance of selective processing based on document type for efficiency enhancement and adaptive learning strategies for overall OCR performance improvement, the differentiation between handwritten and machine-printed documents emerges as indispensable.

Automatically categorizing machine-printed and handwritten documents using advanced machine learning and deep learning techniques necessitates the availability of proper databases.

1.5 In-depth survey of automated shoreline alteration identification methods

In coastal regions, the imperative for automated shoreline management has surged due to mounting challenges posed by climate change, rising sea levels, and heightened human activity. These automated interventions offer swift, data-driven responses crucial for adapting to the dynamic coastal environment. Notably, advanced deep learning methodologies for interpreting image data have gained prominence in recent years. Leveraging remote sensing techniques like Geographic Information Systems (GIS) and predictive modeling enables real-time monitoring of shoreline shifts, erosion patterns, and sediment movement. Early identification of vulnerable areas empowers authorities to take timely actions such as beach nourishment, sediment dredging, and effective tourism industry planning. Automation not only enhances process efficiency but also mitigates human error and reduces response times during critical events such as storms or extreme weather. Moreover, automated shoreline management fosters a more sustainable approach by optimizing resource allocation and striking a balance between development and conservation efforts.

1.5.1 Real life significance of the problem

The pressing need for automated shoreline management in coastal areas stems from escalating challenges posed by climate change, sea level rise, and increased human activity. These automated interventions offer swift, data-driven responses crucial for adapting to the dynamic coastal environment. Recent years have seen a surge in the significance of advanced deep learning methodologies for interpreting image data. Leveraging remote sensing techniques like Geographic Information Systems (GIS) and predictive modeling allows for real-time monitoring of shoreline shifts, erosion patterns, and sediment movement.

Early identification of vulnerable areas empowers authorities to take proactive measures such as beach preservation, sediment dredging, and effective tourism industry planning. Automation not only boosts process efficiency but also minimizes human error and reduces response times during critical events such as storms or extreme weather. Furthermore, automated shoreline management promotes a more sustainable approach by optimizing resource allocation and balancing development with conservation efforts. Embracing automated changes in shoreline management is crucial for ensuring the resilience and longevity of these vital coastal areas.

Recent advancements in deep learning and remote sensing technologies have significantly contributed to the development of automated shoreline change detection models. Driven by the real-world significance of this research area, various researchers have designed numerous deep learning and traditional machine learning-based shoreline change detection methods. These methods incorporate diverse parameters extracted from multiple types of image data, including satellite and optical data. The extraction of these parameters often involves the use of various software tools such as Sentinel

Application Platform (SNAP), Quantum Geographic Information System (QGIS), and the American Multinational Geographic Information System (ArcGIS).

In my study, I have conducted a comprehensive survey of prevailing automated shoreline detection techniques, aiming to provide researchers with a thorough understanding of contemporary technologies in this domain. I offer insights into the optimal types of image data utilized for this specific objective, along with the pertinent parameters selected for extracting information from the image data.

Chapter 2

Literature survey

2.1 Fruity Hub: A diverse collection of fruits created for edibility estimation:

In[8], the realm of agriculture, the adverse impacts of plant diseases on crop yield are a significant contributor to economic losses globally. Among various crops, citrus fruits stand out as essential sources of vital nutrients, such as vitamin C, and are integral to diets worldwide. Regrettably, the prevalence of diseases in citrus crops severely undermines both the quantity and quality of the produce. Leveraging cutting-edge computer vision and image processing technologies, considerable advancements have been made in the detection and classification of plant diseases. To aid in the efforts, a specialized dataset has been curated, featuring an extensive image gallery that captures both healthy and diseased states of citrus fruits and leaves. The collection is designed to empower researchers to harness advanced computer vision techniques to preempt and combat these diseases effectively. The dataset specifically addresses several common citrus afflictions, including Blackspot, Canker, Scab, Greening, and Melanose, providing a comprehensive resource for disease recognition and analysis. It comprises 759 images, representing both healthy and unhealthy conditions of citrus fruits and leaves. Each image is meticulously formatted with dimensions of 256 x 256 pixels and a resolution of 72 dpi, ensuring detailed visual data for accurate analysis. The images were meticulously collected from the Sargodha region—a tropical locale in Pakistan renowned for its citrus production—under the expert supervision of Dr. Basharat Ali Saleem, an Endeavour Executive Fellow at the Curtin University's Horticulture Research Laboratory in Postharvest Australia, Bentley. The dataset stands as a testament to the collaborative effort in advancing agricultural practices and disease management through technological innovation.



a. Canker Disease



b. Black spot disease



c. Greening disease





d. Scab disease e. Healthy

Example 1. Examples of the images that included in the "Detection and classification of citrus diseases in agriculture based on optimized weighted segmentation and feature selection" Database, a. Canker disease, b. Black spot disease, c. Greening disease, d. Scab disease and e. Healthy.

In[9] the field of agriculture, plant diseases constitute a major impediment to productivity, inflicting significant economic damages. Guava, recognized globally for its rich vitamin C content, is no exception, with various diseases adversely affecting its yield and quality. To combat the issue, advancements in computer vision and image processing have been instrumental in facilitating the precise recognition and diagnosis of plant diseases. further, a comprehensive dataset has been compiled, consisting of images of guava fruits and leaves, both healthy and diseased. The resource is meticulously designed to support the development of automated systems that enable researchers to accurately predict and manage diseases affecting guava plants. The dataset includes representations of four prevalent guava diseases: Phytophthora, Red Rust, Scab, and Styler and Root Rot, along with images of disease-free leaves for comparative analysis. The dataset is divided into two distinct types: the original dataset, containing 527 images, and an augmented dataset, which expands this number to 4899 images through image processing techniques to enhance model training capabilities. Each image is standardized at a resolution of 512x512 pixels, providing high-quality visual data for detailed analysis.

The images were meticulously collected from the guava gardens of Bangladesh Agricultural University in Mymensingh, Dhaka, Bangladesh, with the collaboration of domain experts and the plant research center. This dataset not only serves as a vital tool for researchers in the field of agricultural disease management but also showcases the potential of integrating advanced imaging technologies with botanical research to mitigate the impacts of plant diseases globally.



a. Phytophora



b. Red rust



c. Scab



d. Styler end rot



e. disease free leaf



f. disease free fruit

Example 2. Examples of the images that included in the "A comprehensive guava leaves and fruits dataset for guava disease recognition" database, a.Phytophora b. Red rust , c. Scab, d. Styler end rot ,e. disease free leaf, f. disease free fruit.

In[10] the agricultural sector, the rapid and accurate classification of fruits based on quality parameters remains a critical yet unmet need. This challenge continuously captures the interest of the research community, particularly in the realms of machine learning and deep learning, where recent advancements have significantly bolstered capabilities in classification and object detection. Understanding the foundational need for clean and comprehensive datasets in developing precise and robust machine learning models suitable for real-time applications, scientists have meticulously compiled a specialized image dataset of Indian fruits. The dataset is specifically tailored to reflect quality parameters essential for both domestic consumption and export markets. The selected fruits for this dataset include apple, banana, guava, lime, orange, and pomegranate, chosen for their economic significance and high consumption rates. To facilitate diverse training and testing scenarios, the dataset is meticulously organized into three distinct categories: Good quality fruits, Bad quality fruits and Mixed quality fruits. Each category contains subfolders for the six types of fruits, amassing over 19,500 processed images. The structured arrangement allows for granular analysis and benchmarking of fruit quality, catering to the nuanced needs of advanced machine learning models. FruitNet dataset serve as an asset for the development, testing, and validation of fruit classification and recognition models, designed not only to enhance

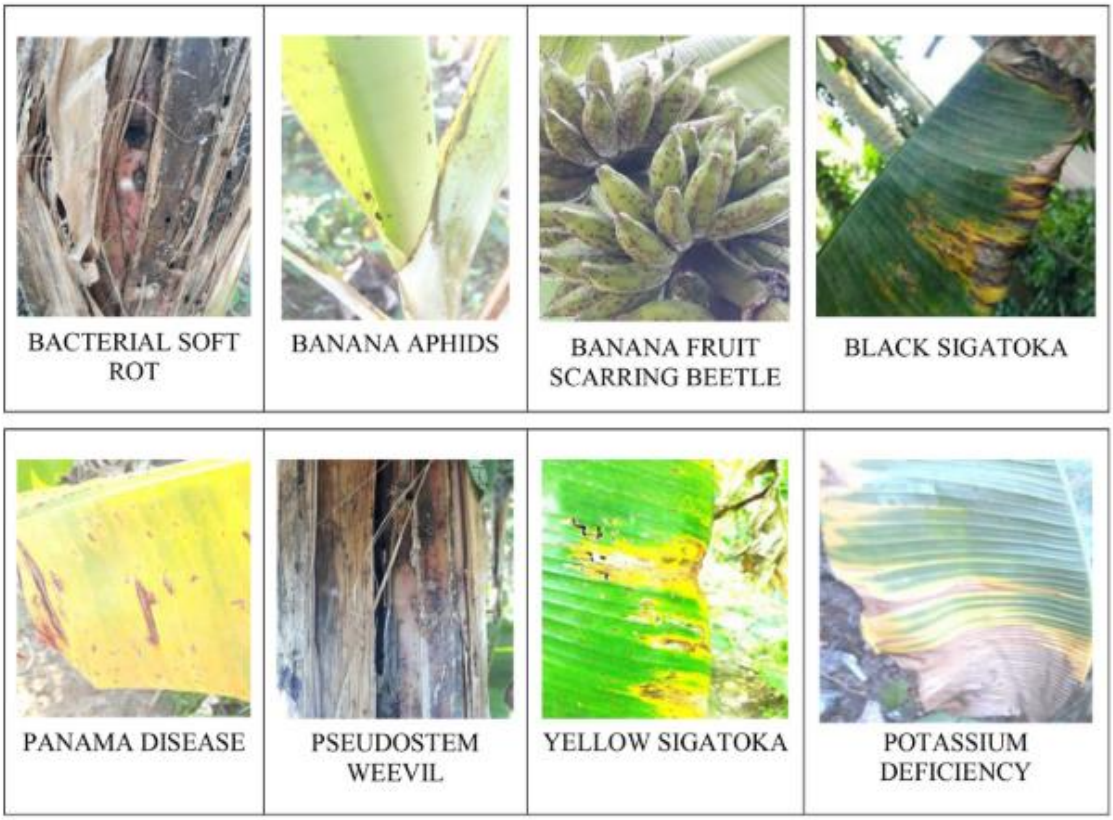
the accuracy of predictive analytics in the agricultural domain but also to support the continuous evolution of machine learning applications in real-world settings.



Example 3. Sample of images from the Jahaji banana (Musa chinensis) dataset.

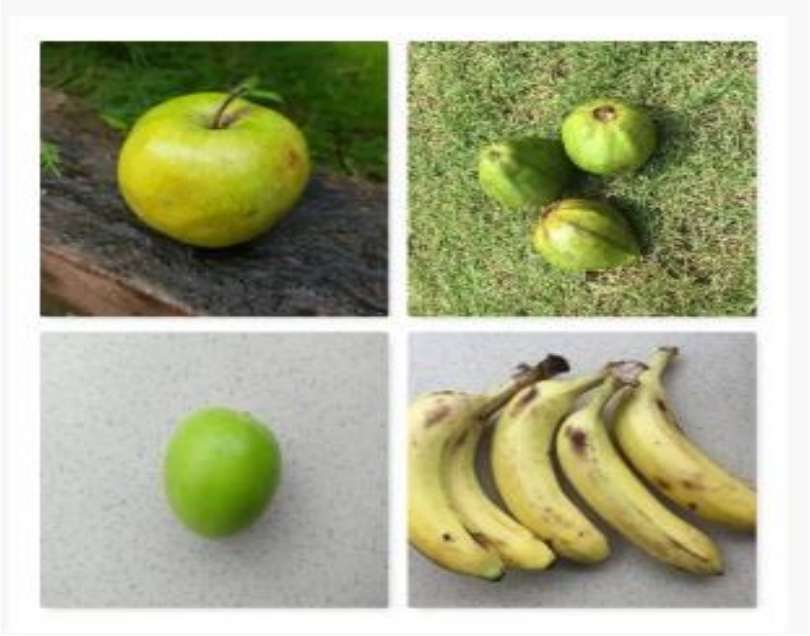


Example 4. Sample of images from the Malbhog banana (Musa assamica) dataset.



Example 5. Sample of diseases that affects the banana plants and the deficiency that incurs production loss in the banana plants.

India holding the distinction of being the second-largest exporter of fruits and vegetables globally, just after China, leads in the production of bananas, papayas, and mangoes [11]. Despite the availability of public datasets for fruits, there remains a significant gap in their ability to categorize fruit quality, a critical factor for export and consumption standards. To bridge this gap, researchers have developed the "FruitsGB" (Fruits Good/Bad) dataset. The primary objectives behind the creation of the FruitsGB dataset are: the dataset specifically targets the top six Indian fruits that are either extensively exported or consumed domestically, Unlike existing datasets that categorize fruits generically, FruitsGB is designed to classify fruits based on their quality, delineating good and bad conditions. The dataset comprises 12,000 high-quality images, categorized into 12 distinct classes representing both good and bad states of each fruit type. For data acquisition, researchers utilized the rear camera of mobile phones to capture the images, ensuring that the dataset reflects realistic and varied conditions. Each of the 12 classes—Bad Apple, Good Apple, Bad Banana, Good Banana, Bad Guava, Good Guava, Bad Lime, Good Lime, Bad Orange, Good Orange, Bad Pomegranate, and Good Pomegranate—contains 1,000 images with a resolution of 256x256 pixels. The images were captured from multiple angles and under diverse backgrounds and lighting conditions to enrich the dataset's robustness and applicability. The focus on the most consumed and exported fruits, this dataset holds significant utility for researchers aiming to advance fruit quality assessment through machine learning and image processing techniques. The comprehensive nature of FruitsGB offers a unique resource for developing and testing algorithms that can effectively differentiate between fruit qualities, which is pivotal for meeting both market standards and consumer expectations.



Example 6. Examples of the images that included in the “FruitsGb: Top Indian Fruits with quality.

The deep neural network which are used for performing real life effectiveness of curated databases:

AlexNet [12], To develop a sophisticated deep convolutional neural network (CNN) to categorize 1.2 million high-resolution images from the ImageNet LSVRC-2010 dataset into 1000 distinct classes. The model demonstrated superior performance on the test dataset, achieving top-1 and top-5 error rates of 37.5% and 17.0% respectively, significantly outperforming the previous benchmarks. The architecture comprises 60 million parameters and 650,000 neurons, organized into five convolutional layers. Some of these convolutional layers are succeeded by max-pooling layers to reduce spatial dimensions and enhance feature extraction. The network also includes three fully-connected layers that culminate in a 1000-way softmax layer to produce the final class probabilities. To expedite training, scientist utilized non-saturating activation functions and an optimized GPU-based implementation of the convolutional operations, greatly increasing computational efficiency. Additionally, to mitigate overfitting, particularly in the fully-connected layers, researchers implemented a novel regularization technique known as "dropout." This method randomly omits a subset of neurons during training, effectively simplifying the model temporarily and preventing co-adaptations on training data.

Further building on this architecture, researchers introduced a modified version in the ILSRV-2012 competition. This variant achieved a top-5 test error rate of 15.3%, markedly better than the second-best entry at 26.2%, confirming the robustness and effectiveness of the approach in a competitive setting.

Vgg16 [13], The groundbreaking study, delve into the intricate relationship between the depth of convolutional networks and their accuracy in the expansive realm of large-scale image recognition. The seminal contribution is a comprehensive examination of increasingly deep networks, utilizing an innovative architecture characterized by compact (3x3) convolution filters. The findings reveal that by extending the network depth to between 16 and 19 weight layers to achieve remarkable enhancements over previous state-of-the-art configurations. The research culminated in a triumphant submission to the ImageNet Challenge 2014, where the experiment clinched both first and second places in the localization and classification tracks respectively, underscoring the potency and precision of the approach. Additionally, to demonstrate that the network representations exhibit impressive generalizability across various datasets, consistently setting new benchmarks. In a move to propel further advancements in the field, two highest-performing ConvNet models openly accessible. The initiative is intended to enrich the research community, offering a robust foundation for exploring deep visual representations in computer vision, and catalyzing future innovations in the field.

ResNet152 [14], identifying pathologies from X-ray imagery represents a crucial yet complex challenge within medical imaging. Contemporary approaches leverage various attributes of chest X-ray images to address this task. However, a critical element often remains unaddressed: the imperative need for comparing corresponding regions within an image to discern anomalies effectively. The research introduces the Attend-and-Compare Module (ACM), a novel framework designed to explicitly capture and quantify the differences between an object of interest and its surrounding context. The model is grounded in the hypothesis that direct, explicit comparison of disparate regions within an image can significantly enhance diagnostic accuracy, particularly in medical imaging where contextual discrepancies are pivotal. The ACM is engineered to be seamlessly integrated into existing deep learning architectures, enhancing their capability by

imbuing them with sophisticated comparative analysis tools. The experiment rigorously evaluated the efficacy of the module by implementing it in three specific chest X-ray recognition tasks, as well as in the COCO challenge for object detection and segmentation. The results uniformly demonstrate marked improvements across all tasks, validating the ACM's utility and effectiveness in enhancing the interpretative power of deep learning models in both medical and general imaging contexts.

MobileNetV2[15], a transformative mobile architecture that sets a new benchmark in performance across a multitude of tasks and scales. MobileNetV2 represents a paradigm shift with its innovative inverted residual structure, which features streamlined bottleneck layers at both the input and output of the residual blocks, in stark contrast to traditional models that employ expanded representations. The architecture capitalizes on lightweight depthwise convolutions within its expansive intermediate layer to efficiently filter features, a methodology that markedly enhances computational efficiency. A key breakthrough in the design was the strategic removal of non-linearities in the bottleneck layers, which the studies show is crucial in preserving the model's representational capacity. The adjustment not only boosts performance but also offers insights into the architectural innovations driving these advancements. Additionally, MobileNetV2 introduces a novel decoupling of the input/output domains from the transformation's expressiveness, laying a robust groundwork for further scholarly exploration also unveil SSDLite, an efficient adaptation of these mobile models for object detection, and present a streamlined version of DeepLabv3, termed Mobile DeepLabv3, for mobile semantic segmentation and rigorous evaluations span across benchmarks such as ImageNet for classification, COCO for object detection, and VOC for image segmentation, where researchers meticulously analyze the trade-offs between accuracy, computational demands (measured in multiply-adds), and model size. The results consistently affirm the superior performance of MobileNetV2, confirming its potential to revolutionize mobile model applications in real-world scenarios.

Convolutional networks form the foundation of leading-edge solutions in various computer vision tasks. Post-2014, the emergence of very deep convolutional networks marked a significant evolution in the field, leading to notable improvements across multiple benchmarks. While larger models and increased computational resources generally correlate with performance enhancements—provided there is sufficient labeled data for training—the demands of computational efficiency and a reduced parameter footprint are critical for applications in mobile vision and large-scale data environments.

Inceptionv3 [16], The research focuses on scaling network architectures to maximize computational efficiency. To employ strategically factorized convolutions and implement rigorous regularization techniques to optimize the usage of computational resources. The experimental framework is evaluated using the ILSVRC 2012 classification challenge's validation set, where the methodology demonstrates significant advancements over existing benchmarks to achieve a top-1 error rate of 21.2% and a top-5 error rate of 5.6% in single-frame evaluations with a model that incurs a computational cost of 5 billion multiply-adds per inference while maintaining a parameter count under 25 million. Furthermore, leveraging an ensemble of four models combined with multi-crop evaluation techniques, scientist report a top-5 error of 3.5% on the validation set and 3.6% on the test set, alongside a top-1 error of 17.3% on the validation set. The results underscore the efficacy of the approach in balancing computational demands with robust performance gains in high-stakes vision tasks.

Xception [17]The function of Inception modules within convolutional neural networks, proposing that these modules act as a transitional architecture between traditional convolution and the depthwise separable convolution process. The latter method involves a sequence where depthwise convolution is followed by a pointwise convolution. Through the lens, a depthwise separable convolution can be conceptualized as an Inception module with an optimally expanded number of towers. Building on this insight, researchers introduce a new deep convolutional neural network architecture, which named Xception. The design innovatively replaces Inception modules with depthwise separable convolutions. The empirical evaluations on the ImageNet dataset reveal that Xception modestly surpasses the performance of Inception V3, the model for which the dataset was tailored. More notably, Xception demonstrates a significant improvement over Inception V3 on a more extensive image classification dataset that contains 350 million images across 17,000 classes. It is critical to highlight that the Xception architecture maintains the same number of parameters as Inception V3. Therefore, the observed performance enhancements can be attributed not to an increase in model capacity, but rather to a more strategic and efficient utilization of the model's parameters. The finding emphasizes the efficacy of the architectural approach in optimizing parameter efficiency while enhancing model performance.

ShuffleNetv2 [18], the field of neural network architecture design, traditionally, the metric of computation complexity, specifically FLOPs (floating-point operations), has served as a primary guide. However, it's increasingly recognized that this metric is somewhat indirect. Actual execution speed, a direct and practical metric, also heavily depends on other factors such as memory access costs and the specific characteristics of the deployment platform. Acknowledging this gap, the research advocates for the evaluation of network performance directly on intended platforms, moving beyond a mere FLOPs-centric view. The research has a series of controlled experiments that have led to the formulation of several actionable guidelines aimed at optimizing neural network design for both efficiency and effectiveness. Building on these insights, researchers introduce a novel architecture, termed \emph{ShuffleNet V2}. For comprehensive ablation studies validate that ShuffleNet V2 sets a new benchmark for balancing speed and accuracy. These experiments demonstrate that the architecture not only advances the state-of-the-art but does so in a manner that is practically applicable across various real-world platforms, making it a superior choice for deployment in diverse settings where performance is critical.

SqueezeNet[19],recent years in deep neural network (DNN) research have predominantly focused on enhancing model accuracy. However, for any given level of accuracy, several DNN architectures can typically be identified that meet this criterion. Among these, smaller DNN architectures present distinct advantages: they reduce the need for extensive communication across servers during distributed training, they lower the bandwidth requirements for transmitting new models from the cloud to edge devices such as autonomous vehicles, and they are more suitable for deployment on hardware with constrained memory resources, like FPGAs. In response to these needs, researchers introduce SqueezeNet, a compact DNN architecture that delivers AlexNet-level accuracy on the ImageNet benchmark with 50 times fewer parameters. Furthermore, by employing advanced model compression techniques, researchers have successfully reduced SqueezeNet's footprint to less than 0.5MB, making it 510 times smaller than AlexNet, thus exemplifying a significant stride toward efficient DNN deployment in bandwidth and memory-limited environments.

DenseNet121 [20], Recent advancements in convolutional network design suggest that networks can be made deeper, more accurate, and easier to train by incorporating shorter connections between layers close to the input and those near the output. Leveraging these findings, Researchers introduce the Dense Convolutional Network (DenseNet), which innovatively connects each layer to every other layer in a feed-forward manner. Unlike traditional convolutional networks that typically have L connections for L layers, each connecting a layer to the next, DenseNet features L(L+1)/2 direct connections. This structure means that for every layer, the feature maps from all preceding layers serve as inputs, and its own feature maps, in turn, feed into every subsequent layer. DenseNets offer several key advantages: they mitigate the vanishing-gradient problem, enhance feature propagation, promote feature reuse, and significantly decrease the number of required parameters. Researchers assessed the DenseNet architecture across four competitive object recognition benchmarks: CIFAR-10, CIFAR-100, SVHN, and ImageNet and the findings show that DenseNets not only achieve substantial improvements over current state-of-the-art models on most of these benchmarks but also do so with less computational demand to reach high levels of performance.

InceptionResNetv2 [21], In deep learning particularly the development of very deep convolutional networks, have led to significant improvements in image recognition capabilities. A notable example is the Inception architecture, which has demonstrated excellent performance while maintaining relatively low computational costs. Additionally, the recent incorporation of residual connections, combined with conventional architectures, achieved state-of-the-art results in the 2015 ILSVRC challenge, performing on par with the advanced Inception-v3 network. The convergence of technologies prompts an investigation into the potential synergies between the Inception framework and residual connections. Research provides compelling empirical evidence that integrating residual connections significantly accelerates the training process of Inception networks and also observe indications that networks designed with residual Inception architectures can marginally outperform their non-residual counterparts, despite having similar computational costs. Furthermore, researchers introduce several new streamlined architectures for both residual and non-residual Inception networks, which enhance the single-frame recognition performance on the ILSVRC 2012 classification task. Moreover, to explore the impact of proper activation scaling, which researchers find crucial in stabilizing the training of very wide residual Inception networks. The approach not only improves training dynamics but also contributes to more robust overall performance, marking a substantial step forward in the design of efficient and powerful convolutional network architectures for image recognition.

NasNetLarge and NasNetMobile [22], In the realm of image classification using neural networks,, substantial effort is traditionally required in the engineering of effective network architectures. The paper explores a method that automates the architecture design process by learning optimal structures directly from the dataset in question. Given the computational intensity of the process on large datasets, researchers propose an innovative approach: first identify an optimal architectural building block, or "cell", on a smaller dataset and then scale the cell for application on a larger dataset. A pivotal aspect of the study is the introduction of the "NASNet search space", specifically designed to enhance the transferability of learned architectures. Experimental strategy involves discovering the most effective convolutional cell on the CIFAR-10 dataset and subsequently deploying it on the ImageNet dataset by replicating the cell multiple times, each instance having unique parameters. The methodology culminates in the creation of the "NASNet architecture". Also to unveil a novel regularization technique, ScheduledDropPath, which significantly bolsters the generalization capability of NASNet

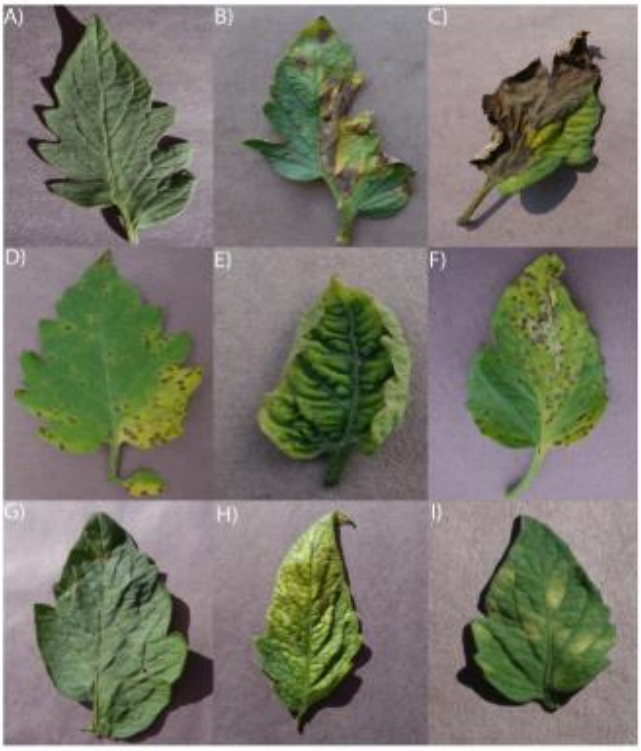
models. The results are compelling: on CIFAR-10, NASNet sets a new benchmark with a 2.4% error rate. On ImageNet, NASNet achieves a top-1 accuracy of 82.7% and a top-5 accuracy of 96.2%, surpassing all previously published models. Notably, NASNet demonstrates a 1.2% improvement in top-1 accuracy over the best existing human-designed architectures while requiring 28% fewer computational resources, as measured by FLOPs. Further evaluations reveal that NASNet models outperform state-of-the-art human-designed models across various levels of computational expense. For example, a scaled-down version of NASNet achieves a top-1 accuracy of 74% on mobile platforms, which is 3.1% higher than its counterparts. Additionally, when NASNet features are utilized within the Faster-RCNN framework, they achieve a new state-of-the-art of 43.1% mAP on the COCO dataset, exceeding previous benchmarks by 4.0%. The comprehensive suite of improvements underscores the efficacy of the approach in pushing the boundaries of neural network design and performance in image classification.

EfficientNetB7[23], Convolutional Neural Networks (ConvNets) are traditionally developed within the constraints of a predefined resource budget, which is subsequently increased to enhance model accuracy as more resources become available. Scientists conduct systematic analysis of model scaling and discover that a balanced scaling of network depth, width, and resolution can significantly improve performance. Building upon this insight, to introduce a novel scaling approach that uniformly adjusts all dimensions—depth, width, and resolution—through a simple, yet highly effective, compound coefficient. Researchers applied the scaling method to enhance models such as MobileNets and ResNet, demonstrating substantial improvements in their performance. Further advancing in research, scientists employed neural architecture search to develop a new baseline network. By scaling the network, a series of models created termed as EfficientNets. The EfficientNet-B7, in particular, achieves state-of-the-art performance with an 84.3% top-1 accuracy on the ImageNet dataset. Remarkably, it is also 8.4 times smaller and 6.1 times faster at inference than the best existing ConvNet models. Moreover, EfficientNets demonstrate exceptional transferability, achieving leading-edge accuracies on other benchmarks such as CIFAR-100 (91.7%), Flowers (98.8%), and three additional datasets used for transfer learning—all while utilizing an order of magnitude fewer parameters. These results underscore the efficacy of the approach in pushing the boundaries of ConvNet design and performance across diverse imaging tasks.

GhostNetv2 [24], Light-weight convolutional neural networks (CNNs) are strategically engineered for deployment on mobile devices, prioritizing faster inference speeds. Traditional convolutional operations are primarily limited to capturing local information within a specific window region, which can constrain performance enhancements. Incorporating self-attention mechanisms allows for the capture of global information; however, this integration typically increases computational load, thereby affecting inference speed. Researchers introduce a novel hardware-friendly attention mechanism, referred to as DFC attention, designed to efficiently execute on commonly used hardware while capturing dependencies between long-range pixels through fully-connected layers. Building upon this mechanism, to present the GhostNetV2 architecture, specifically tailored for mobile applications. The architecture revisits and addresses the expressiveness bottleneck encountered in the previous GhostNet version, enhancing it with the DFC attention mechanism. This enhancement allows the GhostNetV2 blocks to simultaneously aggregate local and long-range information through economically feasible operations. The extensive experimental evaluations attest to the superior performance of GhostNetV2 when compared to existing architectures. Notably, it achieves a 75.3% top-1 accuracy on the ImageNet benchmark with only 167M FLOPs, .

2.2 Greenmednet: A computationally inexpensive hyperparameter optimised dual attention based insulin leaves categorization approach

The[25] pressing challenge of increasing global food production by an estimated 70% by 2050 to nourish a projected population exceeding 9 billion, the detrimental impact of infectious diseases on crop yields becomes a critical concern. Currently, these diseases diminish potential agricultural output by an average of 40%, with some farmers in developing regions experiencing losses up to 100%. However, the pervasive adoption of smartphones, anticipated to reach 5 billion users by 2020, presents a unique opportunity to transform these devices into indispensable tools for agricultural communities worldwide. One innovative application of the technology is the development of mobile disease diagnostics utilizing machine learning and crowdsourcing techniques. Researchers introduce an extensive collection of over 50,000 expertly curated images of both healthy and infected crop leaves, now available through the established online platform, PlantVillage. The launch marks the inception of a dynamic, ongoing crowdsourcing initiative aimed at empowering computer vision technologies to address and mitigate yield losses in crops due to infectious diseases. Through the pioneering effort, scientists setting the stage for advanced agricultural practices that harness the power of technology to secure food sustainability for future generations.



Example 7. Examples of different phenotypes of tomato plants. A) Healthy leaf B) Early Blight (Alternaria solani) C) Late Blight (Phytophthora Infestans) D) Septoria Leaf Spot (Septoria lycopersici) E) Yellow Leaf Curl Virus (Family Geminiviridae genus Begomovirus) F) Bacterial Spot (Xanthomonas campestris pv. vesicatoria) G) Target Spot (Corynespora cassiicola) H) Spider Mite (Tetranychus urticae) Damage included in "An open access repository of images on plant health to enable the development of mobile disease diagnostics" database.

Cassava[26] stands as the second-most crucial source of carbohydrates in Africa, serving as a vital crop for food security among smallholder farmers due to its resilience in harsh growing conditions. Despite its importance, over 80% of household farms in Sub-Saharan Africa that cultivate this crop face significant yield reductions due to viral diseases. Traditional disease detection methods involve labor-intensive processes where farmers must rely on government-funded agricultural experts for plant inspections and diagnoses. The approach is not only resource-intensive but also struggles with scalability and high costs. Moreover, the technological constraints faced by farmers, particularly the usage of mobile-quality cameras and low-bandwidth conditions, pose additional challenges to implementing effective disease management solutions. In response to these challenges, this competition presents a dataset of 21,367 labeled images that were collected during a regular survey in Uganda. The majority of these images were sourced directly from farmers, who captured photos within their fields, providing a realistic depiction of the typical scenarios faced by these growers. The images were then expertly annotated by professionals at the National Crops Resources Research Institute (NaCRRI) in collaboration with the AI lab at Makerere University, Kampala. The dataset not only reflects the real-world conditions under which farmers operate but also serves as a critical tool for developing data-driven solutions to diagnose and manage cassava diseases effectively.







a. Cassava Bacterial Blight b. Cassava Brown Streak Disease c. Cassava Green Mottle



d. Cassava Mosaic Disease



e. Cassava healthy leaves

Example 8. Examples of the images that included in the "cassava-leaf-disease-classification" dataset.

India[27] faces a significant agricultural challenge, losing approximately 35% of its annual crop yield to plant diseases. The complexity of early disease detection is exacerbated by a scarcity of laboratory infrastructure and specialized expertise. In response to these constraints, the paper investigates the application of computer vision techniques for scalable and early detection of plant diseases. A critical bottleneck in the deployment of vision-based disease detection systems is the absence of a large-scale, non-laboratory dataset. Addressing this gap, PlantDoc, a comprehensive dataset specifically designed for visual plant disease detection. PlantDoc encompasses 2,598 data points, spanning 13 different plant species and up to 17 disease classes. The dataset was compiled through rigorous efforts, involving approximately 300 human hours dedicated to annotating images sourced from the internet. To validate the utility of PlantDoc, researchers developed and tested three distinct models tailored for plant disease classification. The experimental results are promising, demonstrating that models trained on the PlantDoc dataset can achieve a classification accuracy improvement of up to 31%. The significant enhancement highlights the potential of PlantDoc to lower the barriers to entry for employing computer vision techniques in the domain of plant disease detection, offering a scalable solution to a critical agricultural challenge.



Example 9. Samples from various classes in the PlantDoc Dataset show the gap between lab-controlled and real-life images.

Triplet loss functions[28] have emerged as a potent tool in enhancing the accuracy of One-shot Learning tasks, particularly since the adoption in numerous projects from 2015 for applications in face recognition and object classification utilizing Siamese networks. Researchers have applied the methodology to two specific vegetation-related tasks, leveraging self-collected image databases to address significant ecological and agricultural challenges. The first task targets the detection of plant diseases across 25 classes encompassing five different crops: grapes, cotton, wheat, cucumbers, and corn. The initiative is driven by the need to mitigate harvest losses—a critical issue affecting both large agricultural enterprises and small-scale rural families. The second task focuses on the identification of five classes of moss species, which play a crucial role as natural bio accumulators in environmental monitoring programs. Accurate identification of these moss species is crucial for the effective preprocessing of samples in such programs. For both tasks, researchers experimented with various deep learning architectures and methodologies. The findings indicate that a Siamese network architecture, employing a triplet loss function and integrated with a MobileNetV2 base network, yielded the most impressive results. Specifically, the configuration achieved an average accuracy of over 97.8% in plant disease detection and 97.6% in moss species classification, showcasing the effectiveness of this approach in addressing both agricultural and environmental challenges through advanced machine learning techniques.



Example 10. Example of the images (cotton, wheat, corn, cucumbers, grape) included in the "One-Shot Learning with Triplet Loss for Vegetation Classification Tasks" database.

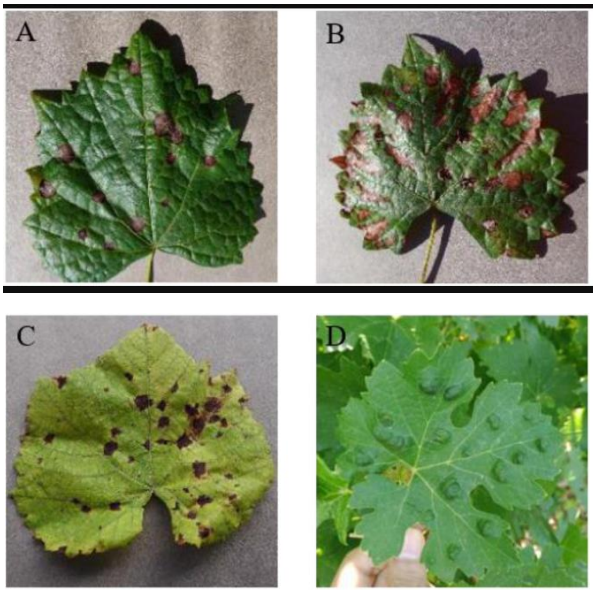
The task[29] of diagnosing plant diseases from their visual manifestations presents a compelling research avenue within agricultural science, wherein methodologies from the field of machine learning are particularly applicable. The article details the development and assessment of a prototype system designed for the detection and classification of rice diseases, using images of affected rice plants. The system was refined through a comprehensive experimental analysis of various image processing techniques. The focus of the research is on three specific rice plant diseases: Bacterial leaf blight, Brown spot, and Leaf smut. Images of diseased rice plants were captured in situ using a digital camera. The experimental setup involved a detailed evaluation of four background removal techniques and three segmentation strategies. A novel segmentation approach—centroid feeding based K-means clustering—was proposed to precisely isolate the diseased portions from the leaf images. The segmentation effectiveness was further enhanced by an additional step that involved the removal of green pixels within the diseased areas. Feature extraction was conducted across three principal categories: colour, shape, and texture, enabling a comprehensive profile of the disease signatures. For the classification tasks, researchers employed a Support Vector Machine (SVM) model, configured for multi-class classification. The system demonstrated a high accuracy rate of 93.33% on the training dataset and 73.33% on the test dataset. Further validation through 5-fold and 10-fold cross-validation processes yielded accuracies of 83.80% and 88.57%, respectively. The results underline the efficacy of the developed prototype in accurately classifying rice diseases, showcasing its potential utility in practical agricultural settings.



Example 11. Different Types of Rice Diseases included in the "Detection and Classification of Rice Plant Diseases " database.

In the agribusiness sector[30], accurate identification of plant diseases is crucial due to the significant economic repercussions associated with misdiagnosis, including substantial losses in both crop yield and market value. Detecting diseases in leafy plants, particularly those belonging to the economically significant cucurbitaceous family—which encompasses 965 species and is a cornerstone of global vegetable production—demands extensive expertise, labour, and processing time. Given the vast scale of production and the high economic stakes, early detection and treatment of diseases within this family are imperative to prevent catastrophic losses. To this end, leveraging advanced deep learning techniques, such as Convolutional Neural Networks (CNNs), offers a promising solution. CNNs can be effectively employed to analyze images of plant leaves, which are often the first and most visible site of many plant diseases. By utilizing leaf images as the primary diagnostic material, CNNs can facilitate early and accurate disease detection, thus safeguarding production and minimizing economic impact in the food industry.

Grape cultivation[31] faces significant challenges from diseases such as Black rot, Black measles, Leaf blight, and Mites, which critically affect yields. Despite the severity of these issues, current research lacks effective real-time detection methods for grape leaf diseases, impacting the health and productivity of grapevines. To address the gap, the paper introduces a real-time detection system for grape leaf diseases utilizing advanced deep convolutional neural networks. Initially, researchers enhanced the available data by expanding grape leaf disease images using digital image processing techniques, resulting in the creation of the Grape Leaf Disease Dataset (GLDD). Leveraging the GLDD, researchers developed a sophisticated deep learning model, the Faster DR-IACNN, which incorporates enhancements to the Faster R-CNN framework. This model integrates the Inception-v1 module, Inception-ResNet-v2 module, and Squeeze-and-Excitation (SE) blocks to significantly boost its feature extraction capabilities. The experimental evaluation of the Faster DR-IACNN model demonstrates a mean Average Precision (mAP) of 81.1% on the GLDD, with a detection speed of 15.01 frames per second (FPS). The results affirm the effectiveness of the Faster DR-IACNN as a viable real-time diagnostic tool for grape leaf diseases. Furthermore, the principles and methodologies applied in this research offer potential pathways for developing similar detection systems for other plant diseases, providing a broader impact on agricultural disease management.



Example 12. Four common types of grape leaf diseases. **(A)** Black rot. **(B)** Black measles. **(C)** Leaf blight. **(D)** Mites of grape.

The integration[32] of deep learning into crop disease classification represents a dynamic research area necessitating extensive image datasets. Notably, eggplant (Solanum melongena), a vital agricultural commodity, is prone to several severe diseases that impede its production. The absence of a comprehensive dataset for the diseases has prompted the research initiative to develop a standardized image dataset under both laboratory and field conditions for the five principal diseases affecting this crop. Researchers employed the pre-trained Visual Geometry Group 16 (VGG16) architecture, a well-regarded model in the field of deep learning. To enhance the robustness of the dataset, multiple color spaces by converting images into Hue Saturation Value (HSV), YCbCr, and grayscale. Empirical results were particularly promising for images in RGB and YCbCr formats captured in field conditions, achieving a classification accuracy of 99.4%. The dataset was further assessed using various renowned deep learning architectures to ensure its effectiveness and versatility in different analytical contexts. Furthermore, utilizing the VGG16 model as a feature extractor, specifically harnessing features from the 8th convolutional layer. The extracted features were then applied to a Multi-Class Support Vector Machine (MSVM) for disease classification, yielding accuracies that matched or, in some instances, surpassed those achieved by direct classification methods. The analysis also includes a discussion on the observed variations in interclass accuracy and proposes directions for future research, thereby contributing valuable insights into the field of crop disease detection and classification using deep learning.

The database[33] contains a comprehensive collection of images showcasing both healthy and diseased insulin plant leaves (Chamaecostus cuspidatus), captured in the Ranaghat district of West Bengal, India. The images feature complex backgrounds with elements such as weeds, soil, and other plants, and were taken under various lighting conditions to enhance the robustness of the dataset. The primary purpose of this repository, named "Nature's Diabetes Helpers: Insulin Leaves Repository," is to facilitate the training of deep neural networks for the automatic classification of the leaves into

healthy or diseased categories. This approach aims to improve the accuracy of real-world plant health diagnostics. The photographs were taken using high-quality mobile cameras, including the Samsung Galaxy S20 FE 5G, equipped with a 12MP Wide Rear Camera, an 8MP Tele Camera, and a 12MP Ultra Wide Space Zoom, and the Redmi Note 9 Pro Max, which features a 64MP+8MP+5MP+2MP camera array enhanced with AI technology.

Deep neural networks used for performing comparative analysis with GreenMedNet on newly curated Nature's Diabetes.

The paper[34] critically evaluates the efficacy of hyper-parameter optimization strategies, specifically contrasting grid search and manual search with random search. the analysis, both empirical and theoretical, suggests that random search is a notably more efficient method for hyper-parameter tuning across various models. The empirical findings draw on comparisons with an extensive previous study that employed grid and manual searches to optimize neural networks and deep belief networks. When neural networks were configured via grid search, the results indicated that random search not only matched but often surpassed the grid search in locating equally or more effective models within a significantly reduced computational timeframe. Moreover, when granted an equivalent computational budget, random search demonstrated superior model performance by exploring a broader and more diverse parameter space. For deep belief networks, a combined approach of manual and grid searches was benchmarked against random search across a 32-dimensional configuration space. The outcomes showed that random search yielded comparable performance on four out of seven datasets and outperformed on one, reinforcing its utility. A deeper Gaussian process analysis of the hyper-parameter to validation set performance function revealed that while few hyper-parameters are critical, the significance varies across datasets. The variability renders grid search particularly inefficient for algorithm configuration on new datasets, findings align with the observed success of "High Throughput" methods, which likely benefit from their capacity to assess a vast range of hyper-parameters, most of which exert minimal influence on performance. The escalating complexity and scale of hierarchical models, there is a growing demand for advanced hyper-parameter optimization methods. The study establishes random search as a robust baseline, underscoring its effectiveness and setting a comparative standard for future developments in adaptive (sequential) hyper-parameter optimization techniques.

Cross-entropy[35] is a cornerstone loss function in machine learning, commonly used due to its effectiveness when combined with the softmax function in neural networks. However, the theoretical underpinnings and guarantees provided by cross-entropy and related surrogate loss functions require deeper examination. This paper explores a comprehensive family of loss functions known as comp-sum losses, which encompasses cross-entropy, generalized cross-entropy, mean absolute error, and other variants that share a similar form.

The contribution is twofold. First, the initial H-consistency bounds for the broad class of loss functions. These bounds are non-asymptotic and provide guarantees that cap the zero-one loss estimation error relative to the surrogate loss estimation error within a specified hypothesis set, denoted as H. To demonstrate that these bounds are not only novel but also tight, meaning they accurately reflect the theoretical limits of these loss functions under the conditions specified. Second, a detailed analysis of the minimizability gaps for comp-sum losses. The gaps are crucial for understanding the limitations and

potential of different loss functions within this family. Building on the framework, researchers introduce a novel subset of loss functions termed smooth adversarial comp-sum losses, derived by incorporating a smoothing term into the traditional comp-sum losses, enhancing their applicability in adversarial settings. To validate the theoretical advantages of smooth adversarial comp-sum losses by establishing that they too admit H-consistency bounds. The theoretical validation underpins the development of new algorithms for adversarial robustness, which focus on minimizing a regularized version of these smooth losses. To complement the theoretical findings, researchers conduct a rigorous empirical analysis, includes a comparative study of various comp-sum losses and a series of experiments aimed at testing the effectiveness of the proposed adversarial robustness algorithms. The results are compelling, demonstrating that the methods not only hold up against but also surpass current state-of-the-art techniques in terms of both adversarial robustness and non-adversarial accuracy.In summary, the work not only bridges the gap between theoretical analysis and practical application of loss functions in neural networks but also introduces robust methodologies for enhancing machine learning models' resistance to adversarial attacks.

Adam[36] is a first-order optimization algorithm designed for stochastic objective functions, which utilizes adaptive estimates of lower-order moments to facilitate efficient optimization. The algorithm is particularly straightforward to implement and requires minimal computational resources, making it highly suitable for large-scale problems characterized by substantial data volumes or parameter spaces. Adam's design ensures it remains invariant to diagonal rescaling of gradients and it performs robustly across a wide range of conditions, including non-stationary objectives and those with noisy or sparse gradients. The hyperparameters of Adam are intuitively understandable and generally demand minimal tuning, which enhances its usability in practical settings. The paper also explores the lineage of Adam, tracing its inspiration from related algorithms to elucidate its conceptual underpinnings and innovations. Furthermore, researchers delve into a rigorous theoretical analysis of Adam's convergence properties, establishing a regret bound that aligns with the most competitive results within the framework of online convex optimization. Empirical evaluations underscore the practical effectiveness of Adam, showcasing its superior performance when compared to other stochastic optimization methods across various test scenarios. Additionally, the paper introduces AdaMax, a variant of Adam that leverages the infinity norm to potentially enhance its robustness and applicability under extreme conditions in certain applications. Collectively, these discussions and analyses affirm the value of Adam and its variants as versatile tools in the optimization of stochastic objective functions.

The Exponential Linear Unit (ELU) is an activation function[37] designed to enhance the learning speed and classification accuracy in deep neural networks. ELUs improve upon the characteristics of Rectified Linear Units (ReLUs) and their variants like Leaky ReLUs (LReLUs) and Parametrized ReLUs (PReLUs) by addressing the vanishing gradient problem and allowing for negative values in activations. This negative value capability shifts mean activations towards zero, akin to batch normalization but with reduced computational demands. This shift facilitates faster learning by minimizing the bias shift effect and bringing the normal gradient closer to the natural gradient. Unlike LReLUs and PReLUs, ELUs also provide a noise-robust deactivation state by saturating to a negative value for smaller inputs, which reduces the variation and information propagated forward. The feature uniquely positions ELUs to encode the presence of specific input phenomena without equally modeling their absence. Empirically, ELUs have demonstrated not only faster learning rates but also superior generalization performance compared to networks using ReLUs and LReLUs, particularly in deeper networks with more than 5 layers. For

instance, on the CIFAR-100 dataset, ELU-based networks outperform ReLU networks with batch normalization, which notably does not enhance ELU networks. Moreover, ELU networks rank among the top 10 for CIFAR-10 results and achieve the best-reported results on CIFAR-100 without reliance on multi-view evaluations or model averaging. On the ImageNet dataset, ELU networks significantly accelerate learning and achieve impressive classification accuracy, with less than 10% error in single crop, single model evaluations.

Deep neural networks (DNNs)[38] have increasingly become a cornerstone in solving complex real-world problems across various emergent domains, supported by the continuous evolution of deep learning (DL) architectures. Central to the operational efficacy of these architectures are the activation functions (AFs), which facilitate intricate computations across the hidden and output layers of DL models. The paper provides a comprehensive survey of the existing activation functions deployed in deep learning applications, underscoring the latest trends and their practical applications. The distinctive contribution of this survey lies in its extensive compilation of activation functions used across DL applications, paired with a critical analysis of current trends in their practical deployment versus theoretical advancements documented in the literature. The survey serves as a valuable resource for researchers and practitioners alike, offering insights that assist in the informed selection of optimal activation functions tailored to specific applications. The paper is particularly timely, as it addresses a gap in the existing literature where most studies tend to reiterate similar findings without a consolidated analysis of practical application trends. The first paper to juxtapose these trends with established research outcomes, providing a holistic view of activation function usage in contemporary deep learning frameworks. The insights garnered here are poised to influence decision-making processes related to activation function selection, aiming to enhance the performance and applicability of deep learning models in real-world settings.

The selection[39] of an appropriate kernel is a pivotal factor in the performance of many machine learning algorithms, yet it often remains a manual choice for the practitioner. The paper explores an alternative approach by employing training data to inform kernel selection within a predefined family of kernels. Specifically, focuses on non-negative linear combinations of p base kernels, traditionally constrained by trace or L1 regularization. Researchers propose a novel methodology that adopts L2 regularization for the learning of kernels, particularly within the context of regression problems. The study is centered on kernel learning within ridge regression frameworks researchers thoroughly derive the solution to the optimization problem associated with the approach and introduce an efficient iterative algorithm to compute this solution. The core of the theoretical contribution is a detailed analysis based on the stability of the learned kernels, establish learning bounds for orthogonal kernels, noting that these bounds introduce only an additive term O(pp/m) relative to the conventional stability bounds associated with standard kernel ridge regression.

Furthermore, the empirical investigations contrast the effects of L1 and L2 regularization on kernel learning. The results suggest that while L1 regularization may yield modest enhancements when a small number of kernels are used, it tends to deteriorate performance as the scale of the kernel set increases. In stark contrast, L2 regularization consistently enhances performance without inducing any degradation, demonstrating pronounced benefits particularly when the model integrates a large number of kernels. The research not only extends the understanding of kernel learning dynamics but also provides a robust statistical framework for enhancing regression models through

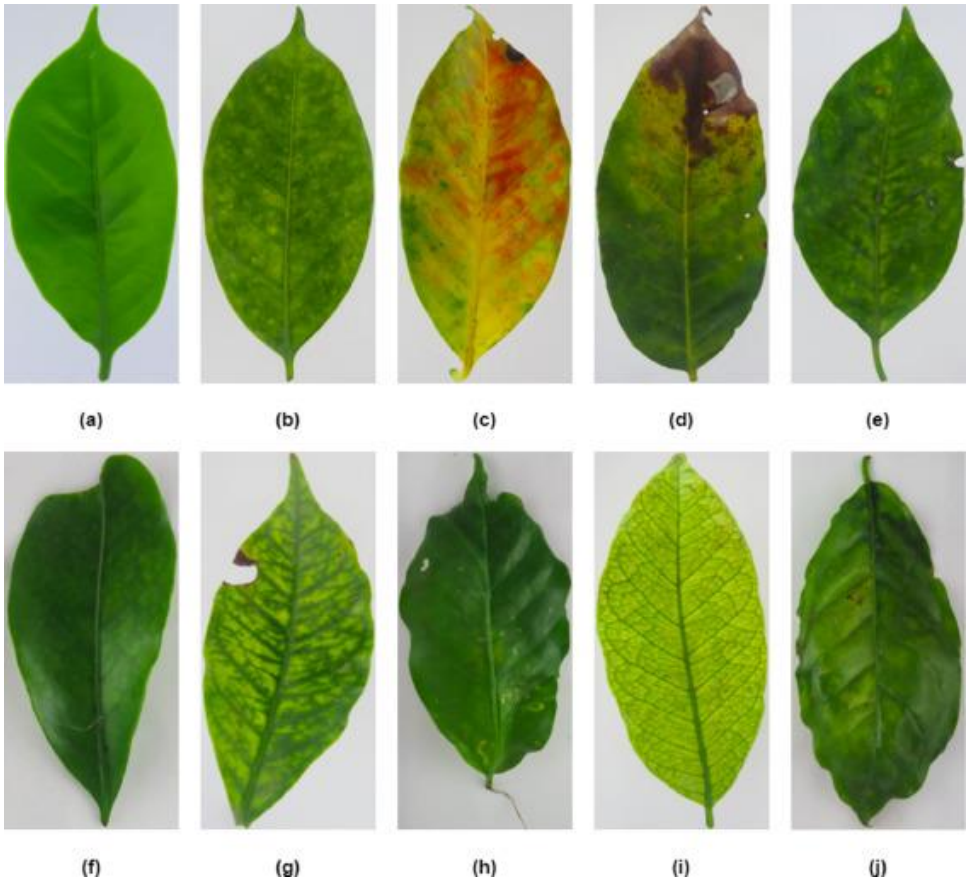
optimized kernel selection, thereby contributing significantly to the field of machine learning.

2.3 Nature's Best vs. Bruised: A Veggie Evaluation:

In the realm of agricultural science[40], the precise classification and identification of fruit and food crops are critical for fostering sustainable growth. With global initiatives underway to enhance food crop production, there remains a pressing need for comprehensive and high-quality datasets tailored to specific agricultural challenges. The article introduces a meticulously curated image dataset focused on various banana plant varieties and their associated diseases, aiming to bridge the data gap in this sector. The dataset encompasses several banana varieties including Malbhog (Musa assamica), Jahaji (Musa chinensis), Kachkol (Musa paradisiaca L.), and Bhimkol (M. Balbisiana Colla), which are significant for both their economic value and susceptibility to diseases. Moreover, the dataset extensively covers prevalent diseases and pathogens affecting these varieties, such as Bacterial Soft Rot, Banana Fruit Scarring Beetle, Black Sigatoka, Yellow Sigatoka, Panama disease, Banana Aphids, and Pseudo-Stem Weevil. Additionally, it includes images illustrating symptoms of Potassium deficiency, a common nutritional problem in banana plants. With over 8,000 processed images, this dataset serves as a robust resource for researchers and students, not only to assist in academic and scientific research but also to facilitate the development of advanced machine learning models that can predict, diagnose, and effectively manage banana plant diseases. By providing access to the comprehensive image dataset, the goal is to empower the agricultural research community to leverage machine learning tools for better crop management and disease mitigation strategies. The initiative also aims to encourage the continued expansion of agricultural datasets and foster innovation in crop disease diagnosis and treatment, contributing to the overall goal of achieving agricultural sustainability. The availability of such targeted datasets is expected to catalyze further research and development in the field, paving the way for more sophisticated and efficient agricultural practices.

The CoLeaf dataset[41], a comprehensive image repository of coffee plant leaves from notable Peruvian coffee varieties—CATIMOR, CATURRA, and BORBON—cultivated in the regions of San Miguel de las Naranjas and La Palma Central in Jaén province, Cajamarca, Peru. Developed to support the application of deep learning technologies in agricultural research, the dataset comprises 1,006 high-quality digital images of coffee leaves, meticulously captured under controlled environmental conditions to ensure consistency and reliability in visual data. The uniqueness of the CoLeaf dataset lies in its detailed classification of leaves based on specific nutritional deficiencies identified by expert agronomists. The deficiencies include a range of essential nutrients such as Boron, Iron, Potassium, Calcium, Magnesium, Manganese, Nitrogen, among others, each associated with distinct visual symptoms affecting leaf health and functionality. By grouping the images according to these deficiency categories, the dataset serves as an invaluable tool for training and validating deep learning algorithms aimed at recognizing and classifying nutritional deficiencies in coffee plant leaves. The strategic collection and organization of the dataset enhance its utility in developing precise machine learning models that can diagnose nutrient deficiencies with high accuracy. The capability is critical for implementing timely and effective nutrient management strategies in coffee cultivation, potentially leading to improved crop health and yield. Furthermore, the CoLeaf dataset facilitates ongoing advancements in agricultural AI by providing a rich source of annotated visual data necessary for refining algorithm performance through rigorous

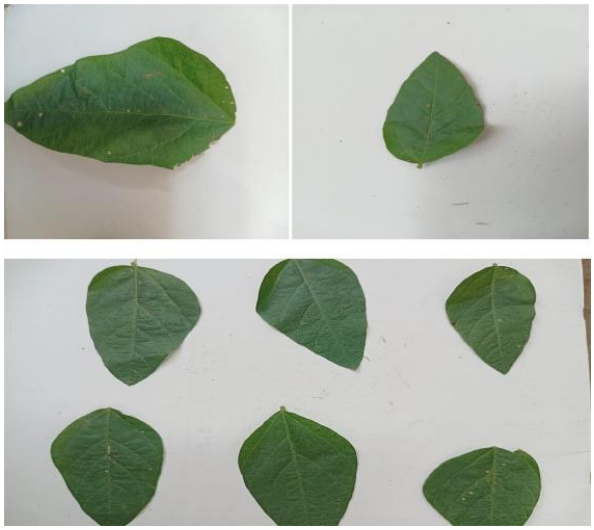
training and testing. In essence, the CoLeaf dataset not only enriches the scientific community's resources for agricultural research but also contributes significantly to the broader efforts of integrating cutting-edge AI technologies into practical farming applications. By enabling more accurate predictions and insights into plant health, this dataset supports the sustainable development of coffee agriculture in Peru and can be adapted for broader agricultural uses worldwide.



Example 13. Images of Healthy leaf (a), Nitrogen deficiency (b), Phosphorus deficiency (c), Potassium deficiency (d), Magnesium deficiency (e), Boron deficiency (f), Manganese deficiency (g), Calcium deficiency (h), Iron deficiency (i), Leaves with more than one deficiency (j) from "CoLeaf-DB: Peruvian coffee leaf images dataset for coffee leaf nutritional deficiencies detection and classification" dataset.

The research[42] introduces a comprehensive dataset focused on the soybean plant, a pivotal agricultural crop in Maharashtra, India. Covering an expanse of approximately 31,050 hectares across key regions including Pune, Satara, Ahmednagar, Solapur, and Nashik, soybean cultivation is a significant agricultural activity, with the plant being sown during three distinct periods: June to July, October to September, and February. The dataset is derived from rigorous image collection efforts spanning two to three growing seasons on multiple farms, aiming to support the advanced applications of machine learning in agricultural disease recognition. Consisting of 3,363 images meticulously organized into seven folders, the dataset provides a valuable resource for the study of

soybean plant health. The images categorize soybean leaves and roots into six distinct classes: I) Healthy plants, which serve as a control group; II) Vein Necrosis, indicating critical vascular damage; III) Dry leaf, showcasing the effects of dehydration or nutrient deficiency; IV) Septoria brown spot, a fungal condition that affects leaf health; V) Root images, essential for studying below-ground health and diseases; and VI) Bacterial leaf blight, a prevalent and damaging bacterial infection. The dataset is particularly designed to facilitate the training and validation of deep learning algorithms geared towards the precise recognition and classification of plant health issues. By providing a range of visually documented plant conditions, the dataset enables researchers and students to develop robust models that can predict, diagnose, and offer solutions for managing soybean plant health effectively. The ultimate aim of making this dataset accessible is to enhance academic research and practical applications in the field of intelligent agriculture. By integrating the dataset into the workflows, academics and practitioners can leverage machine learning tools to improve the accuracy of disease detection in soybean plants, leading to more informed decision-making in crop management. The initiative not only supports sustainable agricultural practices in one of India's most vital farming regions but also contributes to the global efforts in advancing agricultural technology through data-driven insights. The dataset thus represents a significant step forward in the integration of AI in farming, promoting healthier crops and more efficient agricultural outputs.



a. Healthy leaf with single and multi-image



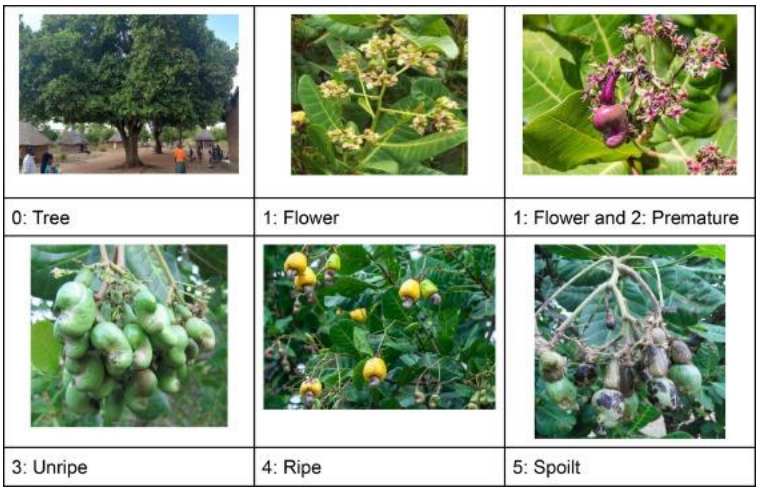
b. Single leaf and Multi-leaf of Septoria Brown disease

Example 14: Images of healthy and diseased leaf from "An India soyabean dataset for identification and classification of diseases using computer-vision algorithms" dataset.

Conventional crop yield estimation methods[43] are often costly, inefficient, and error-prone, leading to inaccurate predictions that can significantly impact farmers' ability to manage their crop production and marketing strategies effectively. Recognizing the need for enhanced precision in this area, a study introduces the development of automated crop yield estimation methods supported by advanced machine learning technologies. However, the efficacy of the methods largely depends on the availability of specialized datasets, which are notably scarce in regions like sub-Saharan Africa. To address the gap, researchers curated and are presenting two high-quality image datasets from Uganda, collected during two distinct crop harvesting seasons spanning nine months from September 2022 to May 2023. Utilizing a high-resolution camera mounted on an Unmanned Aerial Vehicle (UAV), researchers gathered a total of 6,086 images, encompassing 3,000 coffee and 3,086 cashew nut images. The coffee dataset is meticulously annotated to reflect various stages of coffee bean development and condition, classified into five distinct categories: unripe, ripening, ripe, spoilt, and coffee_tree. The classification aids in detailed analyses such as fruit maturity stage assessment and disease diagnosis, which are critical for optimizing coffee production. Similarly, the cashew nut dataset is organized into six comprehensive classes: tree, flower, premature, unripe, ripe, and spoilt. The segmentation facilitates diverse machine learning applications including flowering intensity estimation, crop variety identification, and precise yield estimation. The datasets not only serve to refine the accuracy of crop yield predictions but also enhance the management of crop health and the scheduling of harvesting operations. By enabling the deployment of machine learning models capable of analyzing crop growth stages, health, and overall yield, the datasets provide a foundation for transformative changes in agricultural practices in sub-Saharan Africa. The provision of such datasets is expected to catalyze further research and innovation in agricultural technology, particularly in the development of machine learning tools that can be tailored to the unique challenges and conditions of agricultural sectors in developing regions. Through the initiatives, researchers empower farmers with more reliable and timely data, thereby improving their operational efficiencies and economic outcomes in crop production.



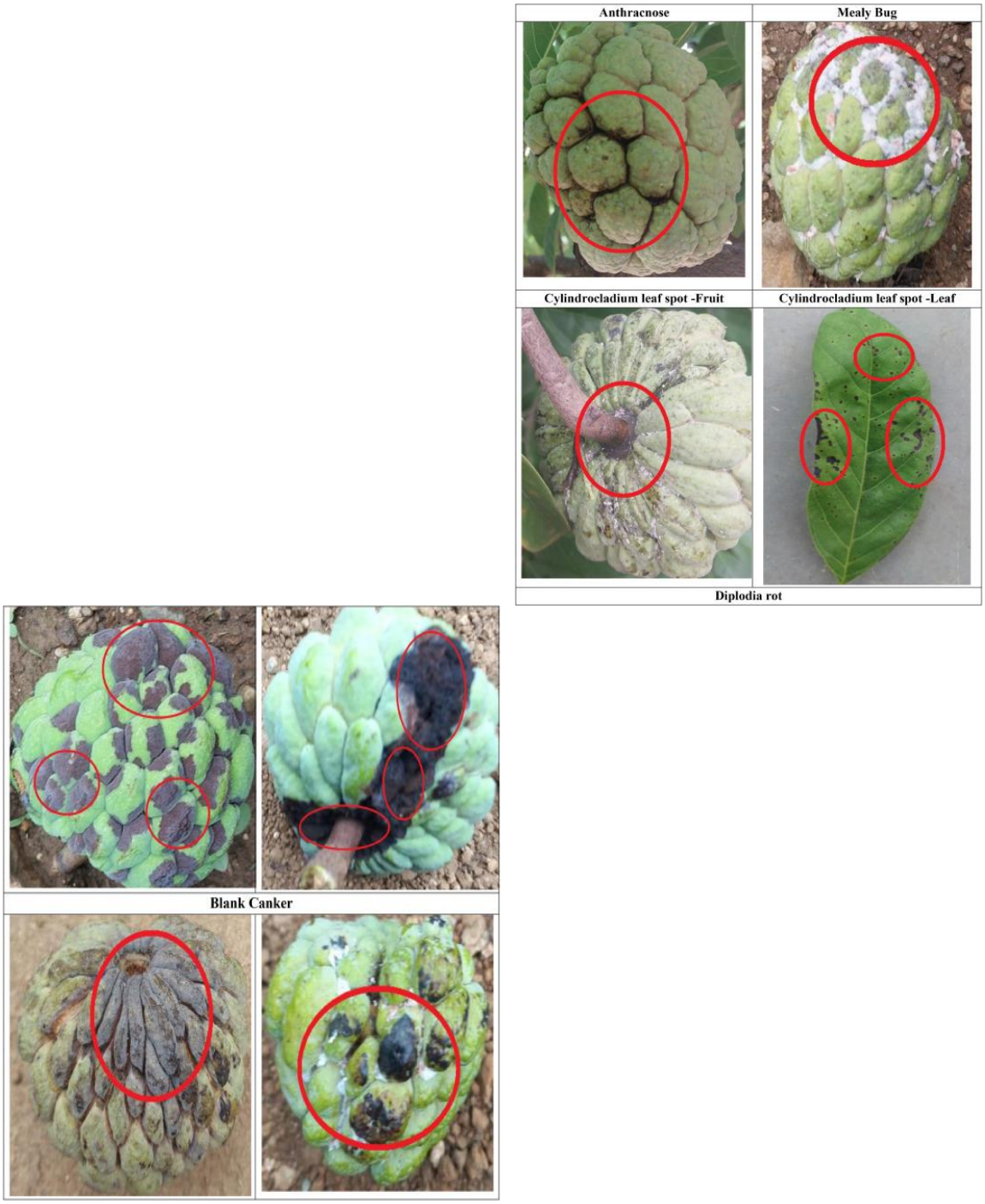
Example15. Sample coffee images showing the different coffee class labels Included in Coffee and cashew nut dataset.



Example16. Sample cashew images showing the five class labels

Included in Coffee and cashew nut dataset

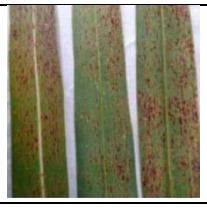
The Custard Apple (Annona squamosa)[44], also known regionally as the sugar apple or sweetsop, is cultivated in diverse climates across India, Portugal, Thailand, Cuba, and the West Indies. To support the advancement of agricultural technology specifically tailored for this fruit, researchers have compiled an extensive dataset comprising 8,226 high-resolution images that detail a variety of disease states affecting the Custard Apple. The dataset is meticulously organized into six primary categories of diseases: Athracnose, Blank Canker, Diplodia Rot, Leaf Spot on fruit, Leaf Spot on leaf, and Mealy Bug, making it an indispensable tool for the refinement of machine learning algorithms aimed at disease detection and classification in Custard Apple plants. The utility of the dataset extends beyond simple disease identification; it serves as a vital resource for developing and enhancing deep learning models, feature extraction techniques, and pattern recognition capabilities. The technological approaches are crucial for improving the precision of automated disease identification systems, which are essential for effective disease management and prevention strategies in Custard Apple cultivation. By enabling more accurate and timely diagnosis of plant health issues, these advanced algorithms help mitigate the impact of diseases, thereby supporting sustainable agricultural practices and improving crop yields. Moreover, the public availability of the dataset promotes a collaborative environment among researchers, technologists, and agronomists. This open access encourages a collective effort towards innovation in plant pathology, accelerating the development of sophisticated diagnostic tools and treatment solutions. Such collaboration is key to fast-tracking advancements in the field and enhancing the overall health and productivity of Custard Apple orchards. The dataset not only enhances existing agricultural practices through improved disease monitoring and management but also facilitates the adoption of cutting-edge AI technologies in the field of horticulture. By integrating the technology into everyday agricultural operations, farmers and researchers can achieve higher efficiency and productivity, leading to more robust Custard Apple production. The initiative ultimately aims to elevate the standards of agricultural practice, ensuring the long-term sustainability and profitability of Custard Apple farming. Through strategic data-driven approaches, researchers setting new benchmarks in the cultivation of this valuable fruit, promoting healthier plants and more abundant yields.



Example 17: Sample images of different custard apple diseases used in "Sample images of different custard apple diseases" database.

Sugarcane[45] serves as a cornerstone of the global sugar industry but is often plagued by various diseases that can dramatically diminish its yield and quality. To combat this, precise and early detection of these diseases is imperative for implementing effective management and prevention strategies. In response to the need, researchers introduce the "Sugarcane Leaf Dataset," a comprehensive collection of 6,748 high-resolution leaf images meticulously classified into eleven distinct categories. These include nine specific disease types—smut, yellow leaf disease, pokkah boeng, mosaic, grassy shoot, brown spot, brown rust, banded chlorosis, and sett rot—along with categories for healthy and dried leaves. The dataset is crafted to enhance the development and refinement of

machine learning algorithms targeted at disease detection and classification in sugarcane. By providing a rich, varied set of imagery, the resource enables the application of advanced computational techniques, such as deep learning, feature extraction, and pattern recognition. The techniques are crucial for improving the accuracy and efficiency of automated disease identification systems, which are pivotal in safeguarding crop health and optimizing yield. The "Sugarcane Leaf Dataset" is not only a technical tool but also a collaborative platform. Its open availability is designed to foster cooperation and innovation within the scientific community, thereby accelerating research into disease control strategies and ultimately enhancing sugarcane production practices globally. The dataset offers a unique opportunity for researchers and practitioners to harness cutting-edge machine learning technologies to advance the state of agricultural disease management. By integrating the dataset into their research, users can explore and implement sophisticated models that can predict and diagnose plant health issues more effectively than traditional methods. This shift towards more advanced diagnostic techniques is expected to lead to better-informed decisions regarding crop treatment and management, significantly reducing the incidence of disease and increasing crop resilience. In conclusion, the "Sugarcane Leaf Dataset" stands as a vital resource for advancing agricultural practices through improved disease detection, monitoring, and management in sugarcane cultivation. Its impact extends beyond mere academic interest, promising real-world applications that enhance productivity and sustainability in sugarcane production. The initiative marks a significant step forward in the integration of artificial intelligence in agriculture, setting a new standard for how crop diseases are managed on a global scale.

				
Smut	Yellow Leaf disease	Pokkah boeng	Mosale (Viral)	Grassy shoot
				
Sett rott	Brown spot	Brown rust	Banded Cholorsis	Dried Leaf
				
Healthy Leaf				

Example 18. Sample images of different sugarcane leaf (Diseases, Healthy, Dried) from Sugarcane leaf dataset

Grapevines[46], a cornerstone of the viticulture industry, face numerous threats from diseases, deficiencies, and pests, all of which contribute to substantial yield reductions. Among these, Flavescence dorée (FD) stands out as a particularly devastating disease due to its high infectivity and significant impact on crop yields. FD is diagnosed by observing symptoms across three critical grapevine organs: the leaf, shoot, and bunch. However, this diagnosis process, typically carried out by scouting experts, is complicated by the fact that many other biotic and abiotic stresses can cause similar symptoms, though not concurrently. The current approach to managing vineyard diseases involves regular monitoring and the application of phytosanitary products across entire blocks of vineyards. The method, while somewhat effective, leads to extensive and often unnecessary chemical usage, raising both environmental and economic concerns. More importantly, it treats the symptoms rather than preventing the onset of diseases. The integration of automatic disease detection technology could revolutionize this traditional approach by enabling early detection of diseases like FD, thus allowing for more targeted treatments. To this end, there is a critical need for a decision support tool that enhances the efficiency and accuracy of vineyard scouting operations. Such a tool would leverage advanced imaging technologies and machine learning algorithms to analyze symptoms on grapevines. By training the algorithms on diverse datasets that capture a range of symptoms and conditions, the tool can learn to differentiate between FD and other similar stressors with high precision. The capability is crucial for ensuring that interventions are timely, appropriate, and economically sensible. Moreover, the adoption of automated detection systems would facilitate continuous monitoring of vine health, providing viticulturists with real-time insights into the status of their crops. The ongoing assessment helps in making informed decisions about when and where to deploy treatments, significantly optimizing resource usage. In conclusion, the development of an automated diagnostic tool for grapevine diseases like Flavescence dorée represents a significant advancement in viticultural practices. By improving the precision of disease detection and treatment, such tools not only promise to enhance the sustainability and profitability of vineyards but also contribute to the broader goal of reducing environmental impact. As the viticulture industry continues to evolve, the integration of technology in disease management will be pivotal in maintaining the health and productivity of grapevines worldwide.



Example 19: Example of the images used in "An expertized grapevine disease image database including five grape varieties focused on Flavescence dorée and its confounding diseases, biotic and abiotic stresses" database.

The integration of machine learning technologies[47] is transforming various industries, notably agriculture, by enhancing precision in tasks such as disease detection and management. The availability of high-quality, extensive datasets is crucial for training effective machine learning models. To address the need for specialized data in agriculture, researchers developed a comprehensive dataset comprising digital photographs of groundnut plant leaves, collected from the Koppal region in Karnataka, India, with expert guidance from a pathologist. The dataset is designed specifically to support the development and validation of advanced deep learning and machine learning algorithms for the classification and recognition of diseases in groundnut leaves. It includes a total of 10,361 images, meticulously pre-processed and organized into six distinct categories based on the condition of the leaves: Healthy Leaves, Early Leaf Spot, Late Leaf Spot, Nutrition Deficiency, Rust, and Early Rust. Each image in the dataset is captured in natural settings, offering a realistic depiction of the conditions typically faced in the field. The approach ensures that the dataset is not only large but also relevant and varied, providing the necessary complexity for training robust models. The pre-processing of these images standardizes the dataset, making it ready for immediate use in machine learning applications. The significance of this dataset extends beyond its sheer size and variety. By facilitating the training of sophisticated algorithms, it enables more accurate and early detection of diseases in groundnut plants. This capability is vital for agricultural producers, as early disease detection is key to implementing timely interventions that can prevent widespread crop damage and yield loss. Moreover, the availability of this dataset encourages collaboration among researchers and technologists, fostering innovation in agricultural AI solutions. It provides a resource that can be used to refine existing models and perhaps inspire new approaches to plant disease diagnosis. Ultimately, the dataset is expected to contribute significantly to reducing losses in groundnut production, enhancing both the efficiency and sustainability of agricultural practices. In conclusion,

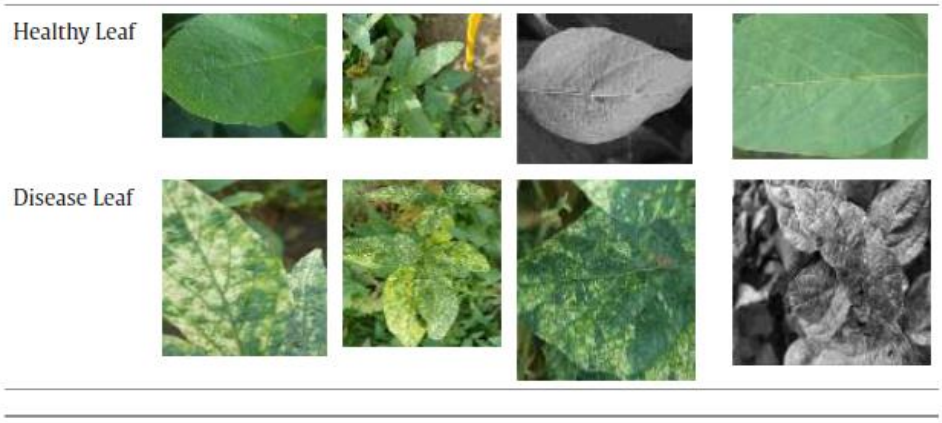
the Groundnut Leaf Dataset represents a valuable asset for the agricultural sector, particularly for stakeholders interested in leveraging cutting-edge AI technologies to improve crop health monitoring and management. It stands as a testament to the potential of data-driven solutions in addressing some of the most pressing challenges in modern agriculture.

			
Early leaf spot	Late leaf spot	Nutrition Deficiency	Rust

Example 20: Images used in "Dataset of groundnut plant leaf images for classification and detection".

The accurate classification and recognition[48] of soybean leaf diseases and healthy leaf identification are critical challenges in agricultural research. To address the challenges, a specialized dataset named "SoyNet" has been meticulously assembled to support the development and validation of advanced machine learning models tailored for this purpose. "SoyNet" consists of over 9,000 high-quality images, capturing both healthy and diseased soybean leaves under real-world conditions, making it a vital resource for researchers in the field. The dataset is thoughtfully structured into two main sub-folders to accommodate different stages of data processing: SoyNet Raw Data and SoyNet Pre-processing Data. The SoyNet Raw Data folder contains original, unprocessed images divided into categories for healthy and diseased leaves. The images were captured in situ from soybean fields using a digital camera equipped on Nikon and Motorola mobile phone devices, ensuring a diverse representation of conditions. The approach facilitates the depiction of various disease symptoms and leaf health statuses in a natural setting, enhancing the dataset's applicability for realistic scenario training. In parallel, the SoyNet Pre-processing Data folder offers images that have been resized to 256x256 pixels and includes grayscale versions of both disease-affected and healthy leaves. The pre-processing step is crucial for researchers who require a ready-to-use dataset for immediate analytical application, enabling efficient load and processing times in machine learning workflows. The collection process involved capturing images from multiple angles and under varied lighting conditions and backgrounds. The diversity is critical as it mirrors the complex dynamics of actual agricultural environments, where lighting and background can significantly impact the visibility of disease symptoms. By incorporating such variations, "SoyNet" ensures that the algorithms trained on this dataset are robust and capable of performing under different field conditions. "SoyNet" is designed not only to enhance the accuracy of disease detection but also to provide a comprehensive tool for the training, testing, and validation of soybean leaf disease classification models. The availability of such a detailed and well-organized dataset accelerates the research and development of diagnostic solutions, potentially leading to more informed and effective disease management strategies in soybean cultivation. In summary, "SoyNet" is a

strategically curated dataset that promises to advance the state of agricultural technology by providing high-quality, real-world data for the enhancement of machine learning models in the classification of soybean leaf health. Its structured approach to capturing and organizing data makes it an invaluable asset for researchers aiming to improve the precision and effectiveness of plant disease diagnosis and management.

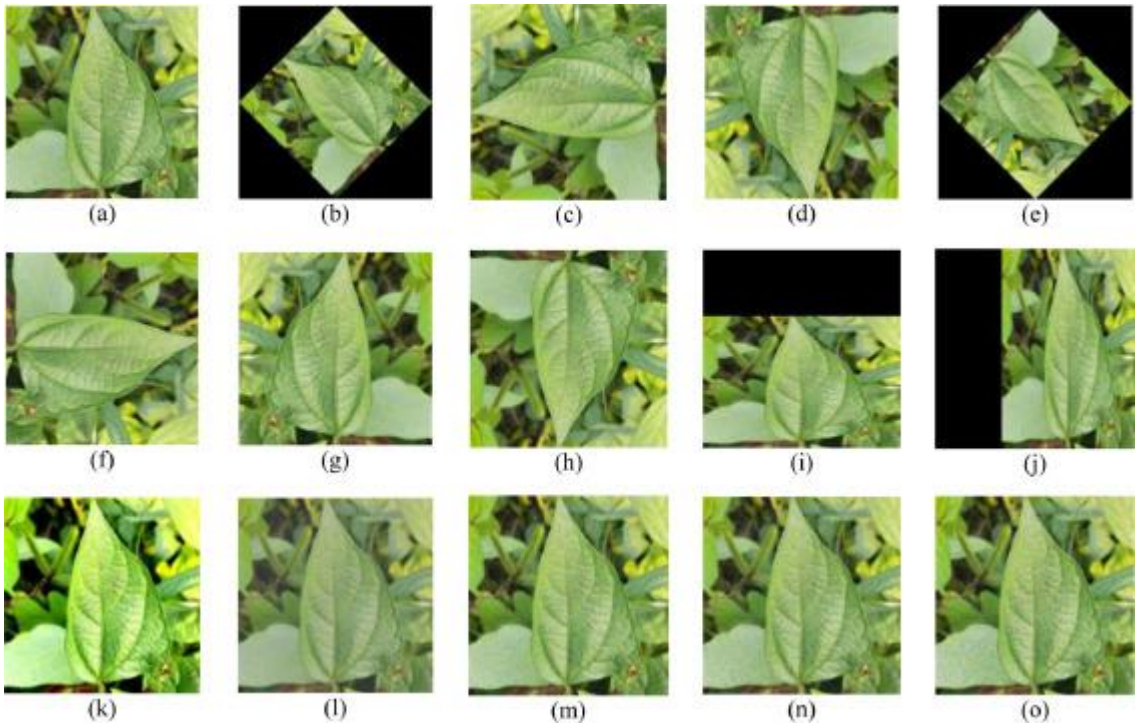


Example 21: Dataset management in SoyNet.

The Black gram Plant Leaf Disease (BPLD) dataset[49] is an essential tool designed to combat the challenges faced by farmers due to prevalent diseases in black gram (Vigna Mungo), also known in India as Urad. Black gram is a crucial pulse crop extensively cultivated across India, contributing significantly to the agricultural sector. However, diseases such as Anthracnose, Leaf Crinkle, Powdery Mildew, and Yellow Mosaic have a substantial impact on crop yields and economic stability for farmers. To address the issues, the BPLD dataset has been developed to leverage advanced image processing and computer vision techniques for the early detection and classification of leaf diseases in black gram. The dataset consists of 1,000 images divided into five distinct categories: four representing specific disease states and one representing healthy plants. Such categorization enables the precise training of machine learning models, particularly deep learning frameworks, which are instrumental in diagnosing and categorizing diseases at an early stage, thus preventing widespread crop damage.

The images within the BPLD dataset were meticulously captured in the real cultivation fields of Nagayalanka, Krishna district, Andhra Pradesh. Utilizing both high-quality cameras and mobile phones, the dataset offers a diverse range of image backgrounds and lighting conditions, reflecting the complexities of real-world agricultural environments. The variability ensures that the algorithms trained on this dataset are robust and adaptable to different field conditions. Post-capture, each image was carefully categorized and processed with the guidance of agricultural experts to maintain accuracy and relevancy in the dataset. The expert involvement guarantees that the dataset not only serves as a reliable resource for training algorithms but also aligns closely with the practical needs and challenges faced by agronomists and farmers. The BPLD dataset is an asset for researchers and technologists focusing on the application of image processing and machine learning in agriculture. By providing high-quality, real-world data, the dataset aids in the development of automated tools that can significantly

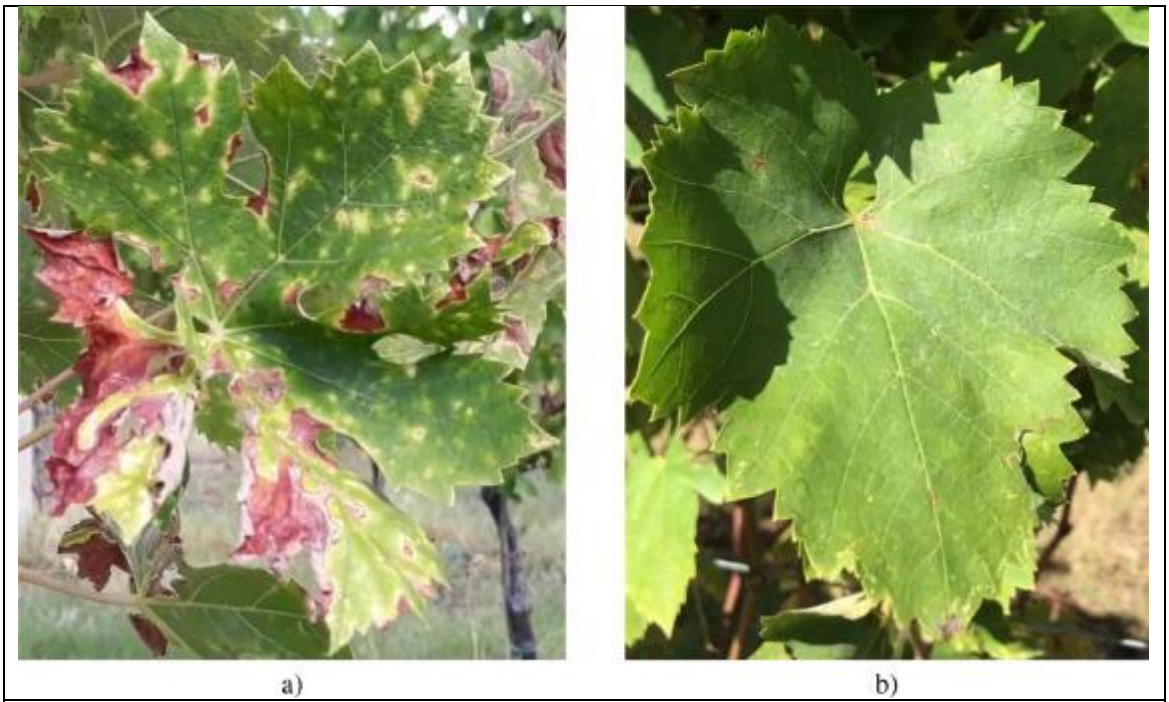
enhance the diagnosis and management of plant diseases. Such tools help in the early intervention of disease treatment, thereby minimizing loss and maximizing yield and profitability for farmers. In summary, the introduction of the BPLD dataset represents a significant step forward in agricultural innovation. It enables the integration of cutting-edge technology into traditional farming practices, offering a promising solution to the perennial challenges of disease management in black gram cultivation. Through the dataset, researchers and practitioners can develop and refine models that will ultimately aid in advancing agricultural productivity and sustainability.



Example 22. Data augmentation techniques (a) Original image (b) 45° rotation (c) 90° rotation (d) 180° rotation (e) 225° rotation (f) 270° rotation (g) vertical symmetry (h) horizontal symmetry (i) shifting vertically by 256 pixels (j) shifting horizontally by 256 pixels, (k) & (l) adjusting various image intensity values (m) gaussian noise (n) salt & pepper noise (o) speckle noise used in " Black gram Plant Leaf Disease (BPLD) dataset for recognition and classification of diseases using computer-vision algorithms".

Esca[50], a pervasive disease in grapevines, poses a severe threat to viticulture, leading to vegetative stress, plant mortality, and substantial economic losses due to decreased production and increased risk of disease spread. Traditional methods for detecting Esca involve time-consuming visual inspections by agronomists, which can delay treatment and control measures. To address the challenges, advanced technological solutions involving image processing, computer vision, and machine learning are being increasingly applied to automate and expedite the disease detection process. In light of the developments, researchers introduce a specialized image dataset aimed at enhancing the capabilities of these modern technological methods in identifying Esca disease in grapevine plants. The dataset comprises images of grapevine leaves categorized into two distinct classes: unhealthy leaves from plants afflicted by Esca and healthy leaves. The categorization supports the development and training of machine learning models

capable of distinguishing between diseased and healthy plant states, thereby facilitating early detection and timely intervention. The dataset has been meticulously compiled in collaboration with the Department of Information Engineering at the Polytechnic University of Marche, Ancona, Italy, and STMicroelectronics, Italy, under the partnership with Umani Ronchi SPA winery in Osimo, Ancona, Marche, Italy. The partnership underscores the dataset's applicability and relevance, ensuring it meets the practical needs of both academic research and vineyard management. The images within the dataset were captured under a variety of conditions to mimic the complexities of real-world scenarios, thereby training algorithms to be robust and effective under diverse environmental conditions. The dataset's structure is designed to support various computational research approaches, including deep learning and feature extraction, which are pivotal in advancing the precision of plant disease classification systems. The valuable resource opens up numerous possibilities for researchers and developers to create innovative applications that assist agronomists and vineyard managers in early disease detection. By integrating this dataset into their systems, they can significantly reduce the time required for disease identification, allowing for quicker and more effective disease management strategies, not only helps in containing the spread of Esca but also minimizes financial losses for wine producers by preserving crop health and productivity. In conclusion, the grapevine leaf dataset is a critical tool that leverages cutting-edge machine learning and computer vision technologies to transform the approach to disease management in viticulture. It embodies the integration of academic research with industry needs, providing a practical solution that enhances disease monitoring and management practices, ensuring sustainability and profitability in the wine industry.



Example of grapevine leaves belonging to different classes: a) Esca disease, b) healthy for classification task.

Example 23. Images used in "A grapevine leaves dataset for early detection and classification of esca disease in vineyards through machine learning" dataset.

Citrus plants[51], celebrated for their rich content of vitamin C and essential nutrients, are a cornerstone crop in tropical regions globally. However, the health and yield of these plants are frequently compromised by a range of diseases, leading to significant economic losses for producers. Recognizing the critical need for early disease detection, recent advancements in image processing and computer vision have been leveraged to develop more proactive and efficient disease management strategies in citrus cultivation. To further these advancements, researchers introduce a comprehensive image dataset focused on citrus fruits, leaves, and stems, specifically curated to aid in the detection and classification of citrus diseases. The dataset encompasses a diverse collection of imagery depicting both healthy and diseased states of citrus plants, affected by common ailments such as Black Spot, Canker, Scab, Greening, and Melanose. The conditions are particularly detrimental to the citrus industry as they directly impact fruit quality and, by extension, market value. The images in the dataset were predominantly captured in December at the peak of disease manifestation, in the orchards of the Sargodha region in Pakistan—a key area for citrus production. The timing aligns with the fruit ripening period when the visibility of symptoms is maximized, thus providing optimal conditions for data collection. The strategic approach ensures that the dataset accurately reflects the challenges faced by growers during critical phases of crop development. Hosted by the Department of Computer Science at the University of Gujrat, the dataset was developed in collaboration with the Citrus Research Center, Government of Punjab, Pakistan. The partnership underscores the dataset's relevance and utility, bridging academic research with practical agricultural needs. By facilitating access to this dataset, the collaborators aim to empower researchers and technologists to harness machine learning and computer vision technologies to create innovative diagnostic tools. The tools are designed to assist farmers by enabling the early detection of plant diseases, thereby allowing for timely and effective intervention. The potential impact of this dataset extends beyond the local farming communities. By providing a rich source of annotated visual data, it serves as a global resource that can be utilized to train and refine algorithms, potentially setting new standards in agricultural practice and plant health management. In essence, this dataset not only supports the immediate needs of disease management in citrus cultivation but also contributes to the broader goal of enhancing agricultural productivity and sustainability through technological innovation. In summary, the citrus plant image dataset represents a significant contribution to the field of agricultural technology, offering a practical solution to combat plant diseases effectively. It exemplifies the successful integration of technological research with agricultural development, aiming to mitigate financial losses and improve the health and yield of citrus crops worldwide.

2.4 BengaliprintDB: A Repository of Machine-Printed Bengali Documents

The BanglaWriting dataset[52], comprises single-page handwritten documents collected from 260 individuals, representing a broad spectrum of demographics and age groups. Each document within the dataset is meticulously annotated, with bounding boxes delineating individual words which are then linked to their corresponding Unicode representations. The dataset encompasses a total of 21,234 words and 32,787 characters, featuring a lexicon of 5,470 distinct Bengali words. Notably, the dataset includes 261 legible overwrites and 450 illegible overwrites. The annotations, including bounding boxes and word labels, are crafted manually, enhancing the dataset's utility in sophisticated applications such as optical character/word recognition, writer identification, and handwriting segmentation. Moreover, it facilitates the analysis of handwriting variations across different ages and genders, making it a comprehensive

resource for both academic research and practical applications in handwritten text analysis.



আমি তো আমাকে নিয়েই ভাববার সময় পাই না।
আপনাদের * গবেষনার জন্য আমি ভাববো
বা আমার একটি চিরকুট যাবে সেটি ভেবে
আপনারা বসে আছেন। আমি আপনাদের
সমস্যাটা বুঝতে পেরেছি তবে সমস্যাটা
সমাধান করার জন্য আপনাদের দু একজন
বিজ্ঞানীর সাথে কথা বলতে হবে।
আর এ কারণে আমি খুব শীঘ্রই
আপনাদের প্রতিষ্ঠানে আসবো।

Example 24. The left image illustrates a handwriting image with word-level bounding-boxes. The labels/words for each bounding-box is presented on the right. The excluded word (second row, second word) is marked using an asterisk (*) used in "BanglaWriting: A multi-purpose offline Bangla handwriting dataset"

The MatriVasha dataset[53], is currently the most comprehensive resource available for the study of handwritten Bangla compound character recognition which includes 120 unique types of compound characters, captured across a robust collection of 306,464 images. The dataset is balanced between gender representations, with 152,950 images from male contributors and 153,514 from female contributors. While primarily designed for enhancing compound character recognition algorithms, the MatriVasha dataset also supports a wider range of scholarly inquiries, including analyses differentiated by gender, age, and regional handwriting characteristics. The compilation of this dataset was executed with a high degree of precision and authenticity, incorporating handwriting samples from diverse age groups and various districts, ensuring equitable representation of both genders and meticulous assembly makes it an invaluable asset for both academic research and practical applications in handwriting recognition technology.

AIBangla addresses[54] the formidable challenges inherent in automatic handwritten Bangla character recognition (HBCR) within the domain of computer vision. The complexity of HBCR arises from significant variations in individual handwriting styles for Bangla characters and the potential for morphological similarities among different characters. To effectively address these challenges, the deployment of advanced convolutional neural network (CNN) architectures is essential for achieving precise character recognition. The field, however, faces limitations due to the lack of sufficiently large Bangla handwritten datasets that offer an extensive range of image samples per character—these are critical for training robust deep learning models. The paper introduces AIBangla, a pioneering benchmark image database designed to enrich the research landscape of HBCR, consists of 80,403 handwritten images, focusing on 50 basic Bangla characters, alongside 249,911 images that capture 171 unique pattern shapes of Bangla compound characters. These images have been sourced from over 2,000 distinct contributors affiliated with various educational institutions across

Bangladesh, ensuring a rich diversity in handwriting samples. AlBangla thus emerges as a comprehensive dataset, uniquely positioned to propel forward the research and development in the field of handwritten Bangla character recognition.

The BN-HTRd dataset[55], derived from the BBC Bangla News corpus, establishes a new benchmark for document-level offline Bangla Handwritten Text Recognition (HTR). The dataset is composed of 788 full-page images contributed by 150 unique writers, making it the most comprehensive collection in its domain. It features 108,147 instances of handwritten words spread over 13,867 lines, encompassing 23,115 distinct words. The dataset is meticulously annotated, providing YOLO annotations for text lines and detailed ground truth annotations for both full-text content and individual words. Additionally, it includes segmented images along with their positional data. The diversity of the BN-HTRd dataset is a significant asset, reflecting a wide array of news categories and incorporating contributions from annotators of varied ages, genders, and backgrounds. The variety introduces a broad spectrum of handwriting styles, enhancing the dataset's utility for developing and benchmarking advanced HTR systems. The dataset's rich annotations and comprehensive scope make it an invaluable resource for researchers and practitioners in the field of machine learning and computer vision, particularly those focusing on handwriting recognition technologies.

The Ekush dataset[56], represents a comprehensive and multifunctional database tailored for the analysis of both online and offline Bangla handwritten characters. The dataset is engineered to support a variety of applications including character recognition, contextual analysis, gender identification, and forensic examination. Dataset features 367,018 instances of characters spread across 122 distinct character classes. Each image in the dataset is augmented with four descriptive captions, enhancing its utility for detailed character studies. Additionally, the dataset provides gender-specific data, with 186,729 character instances contributed by female writers and 180,289 by male writers. The gender-specific aspect not only enriches the dataset's applicability in gender studies within handwriting analysis but also bolsters its comprehensiveness for broader research and application in the field of Bangla handwriting recognition. The Ekush dataset thus stands as a pivotal resource for advancing the state-of-the-art in handwritten character recognition and related technological fields.

2.5 In-depth survey of automated shoreline alteration identification methods

The study[57], conducts a quantitative analysis of shoreline migration patterns on Jambudwip Island within the Sundarban biosphere in the Bay of Bengal, focusing on various timescales to elucidate the interactions between the coastal ecosystem and dynamic sea-land interfaces. The impetus for the research stems from concerns over sea-level rise, primarily due to the melting of polar ice and glaciers, and its impact on coastal environments. The methodology integrates Geographic Information Systems (GIS), Remote Sensing, and statistical analyses to investigate the migration characteristics of the shoreline. The Digital Shoreline Analysis System (DSAS) was employed to quantify shoreline changes over the selected periods. Statistical methods, including the Linear Regression Rate (LRR) and End Point Rate (EPR), were utilized to determine the rates of shoreline change during the years 2011, 2013, 2015, and 2017. Additionally, the Normalized Difference Vegetation Index (NDVI) and a single-band threshold method using the infrared (IR) band were applied to Landsat-7 and Operational Land Imager (OLI) data sets to accurately delineate the shoreline positions. The analysis revealed significant spatial variability in shoreline dynamics; the western part of the island emerged as the

most erosion-prone area, whereas the eastern part exhibited the most accretion. The results indicated pronounced rates of change, with erosion peaking at 49.08 meters per year and accretion at 122.4 meters per year. Consequently, there was a noticeable alteration in the shoreline's length over the study period, which decreased from approximately 11,879.91 meters in 2011 to 10,374.42 meters by 2017. This study underscores the critical need for ongoing monitoring and adaptive management strategies in coastal zones, particularly in ecologically sensitive areas like the Sundarban biosphere.

The erosion and accretion[58] dynamics within the Sundarbans, the world's largest mangrove forest, from 1975 to 2017, employing LANDSAT imagery. The assessment of point-specific shoreline changes is crucial for devising effective management strategies to protect this vulnerable ecosystem and the livelihoods of millions residing in the area. To delineate the permanent waterline from the satellite images, researchers applied the algorithm that calculates the difference between the Land Surface Water Index (LSWI) and the Normalized Differential Vegetation Index (NDVI). The study area encompasses 178 inhabited Mouzas (the smallest revenue unit in the region) and 48 islands along major estuaries stretching from the Hooghly River to the Raimangal River. The Digital Shoreline Analysis System (DSAS) was utilized to predict shore and bank movements. Researchers generated 7,723 transects along the main river channels and an additional 855 along the coastal areas at 100-meter intervals to compute the End Point Rate (EPR), Net Shoreline Movement (NSM), and Net Land Loss/Gain (LL/LG). Analysis of the EPR revealed that 62% of transects along the estuarine channels and 85% along the coast are experiencing erosion. By multiplying the mean EPR by the transect interval, researchers quantified net land loss or gain between transects. Intensive erosion was particularly noted along the eastern bank of the Muriganga River across all surveyed years. Conversely, accretion typically increased landward from the coast across most channels. A significant disparity in erosion and accretion rates was observed between reclaimed Mouzas and the mangrove-covered islands. Specifically, 54% of Mouzas with embankments are retreating at an average rate of 6.14 meters per year, while only 35% of mangrove islands exhibit landward movement, albeit at a slower rate of 4.78 meters per year. The process of new land formation was also more pronounced in mangrove areas (4.78 hectares per year) compared to habited areas (6.84 hectares per year), highlighting the channel stability and erosion resistance provided by mangroves. The findings underscore the protective role of mangrove vegetation against erosion. Consequently, mangrove reforestation emerges as a promising strategy for erosion management in the Sundarbans, emphasizing the need for targeted ecological interventions to sustain this critical habitat and support local communities.

A comprehensive analysis of shoreline changes[59] over a 20-year period in Alappad Panchayath, a coastal village located in the Kollam district of Kerala, India. Nestled between the Arabian Sea and the Thiruvananthapuram-Shoranur (TS) canal, Alappad is a narrow strip of land prominently influenced by both natural and anthropogenic factors. The area is notably rich in heavy minerals, which has led to intensive sand mining activities along the coast, contributing to significant landscape alterations. Employing Geographic Information System (GIS) and remote sensing techniques, the research utilized Landsat 7 ETM+ C1 Level 1 imagery with a temporal resolution of five years to monitor and analyze coastal dynamics. The Normalized Difference Water Index (NDWI) and advanced shoreline delineation methods were applied using the Environment for Visualizing Images (ENVI) and ArcGIS Pro software to precisely quantify the changes in the shoreline. The findings from the detailed examination indicate that Alappad has experienced considerable reductions in land area every five years. The decrement is

primarily attributed to persistent sand mining, coupled with the impacts of marine processes and climate change. The factors collectively exacerbate the vulnerability of the local ecosystem and the livelihoods of the fishing community, which relies heavily on these coastal resources. The study underscores the urgent need for sustainable management practices and regulatory interventions to mitigate the adverse effects of sand mining and to protect the coastal integrity of Kerala and is critical not only for preserving the natural landforms but also for supporting the local economy dependent on fishing and tourism.

Geographic Information System (GIS)[60] and remote sensing techniques to analyze the dynamic geomorphological characteristics of coastal land in Bangladesh, focusing on land erosion and accretion processes across three distinct coastal zones: western, central, and eastern. Utilizing three decades of Landsat satellite imagery spanning from 1985 to 2015, this study comprehensively assesses the coastal land dynamics of the entire country for the first time. The analysis reveals that the rate of land accretion slightly exceeds the rate of erosion, resulting in a net gain of approximately 237 km^2 over the 30-year period, averaging 7.9 km^2 annually. Notably, both erosion and accretion rates are found to be most pronounced in the central coastal zone, surpassing those observed in the western and eastern zones. These findings are crucial for coastal management and underscore the necessity for ongoing monitoring and adaptive management strategies. The study advocates for the consistent application of GIS and remote sensing technologies to track these dynamic changes, providing a robust methodological framework for effective coastal planning and policy-making. Furthermore, the study delineates specific causes of land dynamics within each coastal zone, offering valuable insights that can guide targeted intervention strategies. By understanding the unique challenges and dynamics of each zone, policymakers and planners can devise more precise and effective measures to manage and preserve these critical coastal areas. The proactive approach is essential for mitigating the impacts of natural and anthropogenic factors on Bangladesh's vulnerable coastal regions.

The beach morphology and shoreline dynamics of the Digha-Mandarmani coast[61] in Coastal West Bengal, India—a region noted for its geomorphological activity and ecological diversity within an active coastal belt characterized by pronounced erosion and minimal accretion. Accurate monitoring and prediction of changes in beach morphology and shoreline positions over both short and long timescales are crucial for identifying the specific drivers of these changes and assessing their subsequent impacts. Although manual ground surveying techniques offer high precision, the application of Remote Sensing (RS) and Geographic Information Systems (GIS) provides a more feasible alternative. The technologies are not only comparably accurate but also more cost-effective, efficient, and capable of covering extensive coastal areas, the present study leverages RS and GIS tools, coupled with a fishnet model, to delineate erosion and accretion zones along the Digha-Mandarmani coastline. The approach enables the projection of future shoreline positions and facilitates an understanding of the potential climatic hazards that may impact tourism infrastructure and their sustainability in the region. The significance of this research lies in its potential to inform policy-making for emerging tourist destinations such as Mandarmani. The areas have often developed over time with inadequate adherence to existing coastal zone regulations, frequently lacking the necessary environmental clearances. By providing a detailed analysis of coastal dynamics and potential risks, the study aims to support informed decision-making that can enhance the resilience and sustainability of tourism developments in coastal settings. Such insights are essential for balancing economic interests with environmental

preservation and ensuring the long-term viability of the region's natural and human-made assets.

The Kerala coastline[62] has undergone significant erosion and accretion over recent decades, rendering it susceptible to dynamic coastline changes. Given the high population density and limited land availability in Kerala's coastal zones, addressing coastal erosion is imperative. The paper focuses on developing shoreline maps and analyzing shoreline changes over the past twenty years using sophisticated geospatial software tools. Utilizing ERDAS IMAGINE and ArcGIS 3 software, researchers prepared detailed shoreline maps for the Kodugallur-Chettuva coastal region in Kerala State. The Digital Shoreline Analysis System (DSAS) was employed to quantify the extent of shoreline changes and to pinpoint areas at high risk of further erosion or accretion. The findings indicate that the most pronounced change was observed in Vadanappally, where erosion has altered the shoreline by as much as 726 meters. Conversely, the Koorikuzhi area exhibited the highest accretion with a change of 94 meters. Other critical zones identified include Engandiyoor, Palapetty, Poklai, Aattupuram, Kara, and Azhikode, each presenting significant changes in shoreline and high vulnerability to future shifts. It is paramount to devise and implement strategic coastal management interventions and should ideally blend hard engineering solutions, such as seawalls and groynes, with soft, ecological approaches like beach nourishment and mangrove restoration to mitigate erosion effectively and sustainably. Such integrated coastal management strategies will be crucial in safeguarding the densely populated coastal stretches of Kerala against ongoing and future environmental challenges.

Urbanization[63] is critically linked to the three foundational pillars of sustainable development: economic growth, social progression, and environmental protection. Uncontrolled urban expansion often leads to rapid sprawl, heightened pollution, environmental degradation, and unsustainable patterns of production and consumption. Therefore, a rigorous assessment and a well-defined methodology are essential for effective urban planning. The study aims to delineate spatiotemporal patterns of urban expansion and intensity within two major metropolitan areas in Kerala, India: Thiruvananthapuram and the Cochin city region. To quantify the scale and velocity of urban growth, researchers developed two specific metrics: the Urban Proportional Index (UPI) and the Urban Intensity Index (UII). The indices were calculated using GIS-based buffer analysis, where each buffer zone serves as a fundamental spatial unit for analyzing distance-dependent urban growth behaviours, alongside their associated UPI and UII values over selected time periods. The analysis revealed two distinct phases of urbanization within the study areas, indicating varying dynamics between these two cities. Thiruvananthapuram, as the administrative capital, and Cochin, as the commercial hub, both exhibit urban behaviours that warrant significant attention due to their pivotal roles in the state's overall development. The findings from the study underscore the necessity of targeted urban planning interventions that accommodate both the unique growth patterns and the strategic importance of these cities. The approach is crucial for fostering sustainable urban environments that align with broader developmental objectives while mitigating the adverse effects of unchecked urban sprawl.

Coastal zones[64] are dynamic environments, subject to significant morphological changes due to both natural processes and anthropogenic development activities. The study of shoreline changes has thus become increasingly crucial in recent years, particularly for planning and management in coastal zones. Accurate measurement and monitoring of shoreline dynamics are essential for effective coastal zone management and construction. Researchers assessed the rate of shoreline changes along a 32 km

stretch of the Cuddalore coast, located between the Gadilam and Vellar Rivers. Shoreline mapping was meticulously performed using manual digitization techniques within the ArcGIS software environment. To quantify the changes, researchers employed two analytical methods: the End Point Rate (EPR) and the Net Shoreline Movement (NSM).

The findings indicate a pattern of erosion and sediment deposition along the studied coastal segment. Specifically, the area north of the Uppanar river mouth (from regions A to C and E) is experiencing erosion. Conversely, maximum accretion is observed in the region extending from J to K, with an EPR of 7.6 m/year and an NSM measurement indicating a maximum shoreline advance of 114 meters at transect 61. In terms of erosion, the most significant retreat was recorded at transect 2, with an EPR of -3.8 m/year and an NSM of -57 meters. The results highlight the variable nature of shoreline dynamics across different segments of the Cuddalore coast, underscoring the need for localized coastal management strategies that can adapt to and mitigate these changes effectively.

Shoreline change analysis[65] is a critical task with widespread applications across various fields including setback planning, hazard zoning, erosion-accretion studies, regional sediment budgeting, and predictive modeling of coastal morphodynamics. Traditional ground survey methods for shoreline delineation are often challenging, time-consuming, and impractical for extensive coastal systems. However, advancements in remote sensing and Geographic Information System (GIS) technologies have greatly facilitated the extraction and detection of shoreline changes. Researchers have developed an automated shoreline detection methodology that utilizes histogram equalization and adaptive thresholding techniques. The method was applied to extract the shoreline of the Netravati-Gurpur rivermouth area along the Mangalore coast on the West Coast of India. Satellite imagery from the Indian Remote Sensing Satellite (IRS P6) LISS-III for the years 2005, 2007, and 2010, and IRS R2 LISS-III for 2013, were analyzed using this novel automatic detection technique. The extracted shorelines were subsequently analyzed with the Digital Shoreline Analysis System (DSAS), a specialized GIS software tool. The analysis utilized two statistical techniques to estimate the rates of shoreline change: the End Point Rate (EPR) and the Linear Regression Rate (LRR). The findings reveal distinct patterns of accretion and erosion along different sectors of the shoreline. Specifically, the Bengre spit in the northern sector of the Netravati-Gurpur rivermouth is experiencing accretion with an average rate of 2.95 m/year (EPR) and 3.07 m/year (LRR), and a maximum accretion rate of 8.51 m/year (EPR) and 8.69 m/year (LRR). In contrast, the southern sector, specifically the Ullal spit, is undergoing erosion at an average rate of -0.56 m/year (EPR) and -0.59 m/year (LRR). The results underscore the effectiveness of the developed automatic shoreline detection method and the utility of DSAS in quantifying and understanding dynamic shoreline changes. Such technological advancements are crucial for informed coastal management and planning, enabling more accurate assessments and targeted interventions in vulnerable coastal areas.

A comprehensive long-term analysis[66] of shoreline changes along the Odisha coast in India, covering the period from 1990 to 2015, utilizing geo-informatics. The High Water Line (HWL) was designated as the shoreline marker, identified through the Modified Normalized Difference Water Index (MNDWI) method, shorelines were delineated as vector data from binary raster images generated by employing dynamic local threshold values. The vector shorelines were updated for accuracy in river creeks and mouths. To quantify the rate of shoreline change, researchers utilized the Digital Shoreline Analysis System (DSAS), a tool developed by the US Geological Survey and implemented as an extension for ArcGIS. The Linear Regression Rate (LRR) method was employed within

DSAS to calculate the shoreline change rates. The findings of the analysis revealed significant changes along the Odisha coastline: approximately 196 km (46%) of the shoreline has eroded, while 78 km (18%) remains stable, and 156 km (36%) has accreted. Notably, the districts of Puri and Kendrapara exhibited the most significant erosion, with about 80 km (18.7%) and 41 km (9.5%) of their shorelines eroded, respectively. Conversely, the Bhadrak district displayed the most accretion, with around 37 km (8.5%) of shoreline expansion. In contrast, the Ganjam district showed the least erosion, approximately 8 km (2%), and Puri district had the least accretion. The regional-scale study provides critical insights that can inform sustainable coastal zone management and planning. The detailed shoreline change data are invaluable for coastal managers and researchers, aiding in the development of targeted strategies to address erosion and accretion along the Odisha coast, thereby contributing to the broader goals of sustainable coastal development.

The primary aim [67] was to evaluate shoreline changes in the south Konkan region, specifically within the Sindhudurg district on the west coast of India, achieved through detailed Shoreline Change Detection Analysis (SCDA). SCDA was meticulously conducted using a combination of field excursions, GPS surveys, cross-profiling, and satellite imagery analysis. Topographic sheets were utilized to develop a foundational map. Precise GPS coordinates were recorded at each surveyed location to ensure accuracy and repeatability of the measurements. The collected data underwent rigorous cross-verification and were compared against the Maharashtra Maritime Board (MMB) bathymetric charts to ensure consistency. Satellite imagery from Landsat, spanning from 1991 to 2022, was geometrically corrected to facilitate the extraction and digitization of shoreline data. The images were then georeferenced to enable precise analysis. The Long-term Rate of Change (LRR), End Point Rate (EPR), and Net Shoreline Movement (NSM) metrics were computed using the Digital Shoreline Analysis System (DSAS), which helped in quantifying shoreline erosion and accretion rates. The analysis period extended from 1999 to 2022. The results revealed a negative LRR of -0.66 meters per year, indicating an overall retreat of the shoreline. The EPR also showed a negative trend at -1.03 meters per year. Conversely, NSM demonstrated a significant shift, with an increase up to 69.64 meters, suggesting considerable sediment dynamics along the coast. A notable finding was the development of a sediment belt approximately 815 meters wide, located to the west of the coastal axis during ebbing tide conditions. The analysis indicated that approximately 67.40% of the shoreline remained stable with negligible rates of change. The application of DSAS in this study not only highlighted the dynamics of shoreline migration and sediment transport but also demonstrated its utility as a universal tool that can be adapted for similar analyses globally. The approach could significantly contribute to coastal regulation planning and decision-making processes, offering a methodological framework for other coastal regions to follow.

The study[68], to quantify shoreline dynamics in Hambantota District from 1976 to 2014, utilizing Landsat satellite imagery to delineate eight shoreline positions at intervals spanning 38 years. Advanced image processing techniques such as enhancement, classification, and composite banding were employed within ArcGIS 10.2 to accurately delineate the land-water interface. The precision of shoreline extraction, verified against ground observations and corroborated with Google Earth satellite images, was determined to be 87%. The Digital Shoreline Analysis System (DSAS) facilitated the analysis by projecting 130 transects at right angles to the coastline every 500 meters to measure shoreline changes. Using metrics like the End Point Rate (EPR), Shoreline Change Envelope (SCE), and Net Shoreline Movement (NSM), the findings underscore the coastline's high dynamism, with an average erosion rate of approximately -1.5 meters

per year, and deviations as wide as ±2.48 meters. Notably, erosion rates near the Hambantota port were markedly severe, reaching up to -24 meters per year, reflecting significant alterations linked to the port's construction and operational impacts.

This study [69] on evaluating shoreline dynamics in the Kuwaru coastal region, which is particularly vulnerable due to its composition predominantly of loose sedimentary materials. These materials are highly susceptible to erosion and redeposition in response to environmental disturbances, amplifying the risks associated with shoreline changes. The study utilizes the Digital Shoreline Analysis System (DSAS) to quantitatively assess these changes, which are critical given their impacts on local tourism, fisheries, land stability, and infrastructure. An interdisciplinary methodology integrating remote sensing and Geographic Information Systems (GIS) was employed. Initial data were sourced from topographic maps dated 1995 and multi-temporal satellite imagery spanning 2006 to 2015. The shoreline change was quantified using the End Point Rate (EPR) technique, with the 1995 shoreline data serving as the baseline. This analysis was conducted along transects set at 50-meter intervals perpendicular to the baseline, across the coastal stretch. The findings reveal substantial shifts in the Kuwaru coastline since 1995, with the shoreline retracting over 50 meters landward by 2015. Factors contributing to these shifts include extreme weather conditions prevalent during the East Monsoon season, which produces destructive waves up to 5 meters high impacting the region from the southeast. The findings underscore the urgency for implementing coastal mitigation strategies, both structural and non-structural, to manage and mitigate the dynamic coastal processes observed in the Kuwaru area.

This research[70], in the coastline of Chabahar Gulf along the Oman Sea over a period of forty-two years, employing advanced remote sensing techniques to address the environmental impact of extensive construction along Iran's southern shores. Such developments have significantly altered local geomorphology, influencing erosion and sedimentation patterns. Remote sensing data, recognized as an effective tool for coastal studies, facilitated the examination and interpretation of both qualitative and quantitative changes in coastal landforms, tidal fluctuations, coastal line shifts, and seabed depth. The study utilized various supervised classification methods to analyze multi-temporal satellite imagery from 1972 to 2014. The most precise classification technique was selected to segregate the images into two distinct classes—land and water. The analysis revealed significant coastal transformation within the study timeframe: approximately 1,832,436 square meters previously classified as land were reclassified as water, while about 7,004,844 square meters transitioned from water to land classification. This net change underscores the dynamic nature of coastal zones and highlights the critical need for sustainable management practices to mitigate the environmental impacts of human interventions on coastal ecosystems.

The study[71] of analyzing shoreline dynamics within the Vishakhapatnam district along the Andhra Pradesh coast, aiming to quantify erosion and accretion rates over a 45-year span from 1974 to 2020. Spanning a 135 km coastline divided into four zones—Bheemunipatnam (Zone 1), Vishakhapatnam (Zone 2), Anakapalli (Zone 3), and Yellamanchili (Zone 4)—the research employs multitemporal satellite imagery from Landsat 7 and Landsat 4 & 5, analyzed using the Digital Shoreline Analysis System (DSAS). The methodology involved calculating the rate of shoreline change through metrics such as Net Shoreline Movement (NSM), Shoreline Change Envelope (SCE), End Point Rate (EPR), and Linear Regression Rate (LRR). The analysis revealed significant geological shifts and variations in shoreline positions, indicating an overarching trend of accretion across the studied coastline with an average rate of +1.13 meters per year,

contrasting with a lesser rate of erosion at -0.15 meters per year. Notably, the highest SCE was recorded at 63.4 meters per year and the lowest at 75.25 meters per year in Vishakhapatnam. Furthermore, the study utilized the Multi-output Adaptive Neuro Fuzzy Inference System (MANFIS) technique to predict future shoreline metrics such as EPR, NSM, SCE, and LRR. The predictive capability is essential for ongoing monitoring, planning, and development efforts, as well as for enhancing the decision-making processes of disaster management authorities in the region. The comprehensive findings underscore the dynamic nature of coastal environments and the critical need for informed management strategies to mitigate the impacts of natural and anthropogenic activities on shoreline stability.

The research[72], focused on identifying and quantifying shoreline changes due to abrasion and accretion in Supiori Regency, Indonesia, over a decade from 2013 to 2023 using Landsat 8/9 satellite imagery. Employing the Digital Shoreline Analysis System (DSAS) on ArcMap software, scientists analyzed the Net Shoreline Movement (NSM) and the End Point Rate (EPR) to assess the dynamics of the coastline. The study revealed significant abrasion and accretion across various locations within the region, particularly pronounced in Supiori Selatan District where maximum shoreline movements were recorded at -67.15 meters for abrasion and +92.86 meters for accretion. On average, abrasion ranged between -11.37 to -13.59 meters, while accretion ranged from 9.75 to 15.64 meters. Among the districts analyzed, only Kepulauan Aruri District exhibited a net positive shoreline movement, indicative of predominant accretion. In contrast, the other four districts demonstrated dominant abrasion with negative values. The annual rates of shoreline change due to abrasion and accretion were quantified, with abrasion rates between -1.22 to -1.46 meters per year and accretion rates between 1.05 to 1.68 meters per year. The changes are primarily driven by natural phenomena such as wave action, currents, and riverine inputs, alongside significant anthropogenic impacts resulting from local human activities. The data derived from the study is critical for stakeholders involved in coastal management within Supiori Regency. Given the substantial rates of shoreline change observed, there is an urgent need for comprehensive planning and strategic mitigation measures to manage and potentially reduce the negative impacts of increased coastal erosion and its associated risks.

The study[73], conducts a detailed analysis of coastal dynamics in Tabanan Regency, Bali Province, Indonesia, by utilizing high-resolution satellite data to evaluate coastal change and erosion rates. High-precision satellite imagery from SPOT 5 (2009) with a spatial resolution of 10 meters and SPOT 6/7 (2015) with a resolution of 1.5 meters facilitated an accurate assessment of coastline shifts over the specified period. The results indicate a significant average coastline shift of 13.96 meters within the study timeframe. Additionally, the average annual rate of coastal erosion was determined to be 1.99 meters, highlighting the coast's dynamic and continually evolving nature. The changes, influenced by both natural phenomena and anthropogenic factors, emphasize the urgent need for strategic, data-driven decision-making to address the resultant morphological alterations. The findings provide essential data that supports both local and central governmental bodies in their coastal management efforts. With comprehensive insights into the spatial patterns and rates of coastline changes, these authorities are equipped to develop and implement effective management strategies that aim to preserve the coastal environment while also considering the socio-economic dependencies of the region. This proactive approach is crucial for sustaining the ecological integrity and resilience of coastal areas in the face of ongoing environmental pressures.

A robust combination[74] of remote sensing and Geographic Information System (GIS) technologies, augmented by the Digital Shoreline Analysis System (DSAS), was employed to examine historical shoreline changes and forecast future shoreline positions along Almanarre Beach, which is currently facing significant erosion threats. The study covered the period from 1973 to 2015, during which Almanarre Beach exhibited a mean annual erosion rate of approximately -0.24 meters per year. The most pronounced erosion occurred near Landmark B17, where the highest recorded erosion rate reached -0.86 meters per year. Future projections for shoreline change were also developed using the same methodologies, with anticipated erosion rates of around -0.05 meters per year by 2020 and -0.22 meters per year by 2050. Specific attention was given to the areas around Landmarks B06-08 and B16-18, which are expected to undergo the most severe recession, with rates predicted at -0.89 meters per year and -0.94 meters per year, respectively. The research underscores the efficacy of integrating geospatial techniques with numerical modeling to accurately analyze and predict trends in shoreline dynamics. The findings not only contribute to a deeper understanding of coastal erosion patterns but also serve as a valuable resource for coastal management strategies aimed at mitigating erosion impacts and preserving shoreline integrity.

The coastal environment[75], where the atmosphere, hydrosphere, and lithosphere intersect, represents a distinct and dynamic setting. The coastline serves as a significant linear feature on the Earth's surface, characterized by its vibrant and ever-changing nature. Effective management of coastal zones hinges on the availability of detailed and accurate information about shoreline changes to inform updates to shoreline change charts and natural resource management strategies. Typically, monitoring efforts are concentrated on changes occurring within coastal regions, with the shoreline being a pivotal GIS element due to its capacity to provide extensive insights into coastal dynamics. The paper delves into contemporary satellite-based methods for detecting changes in shorelines, emphasizing the critical importance of these technologies in coastal management. It specifically examines the shoreline transformations in the Cuddalore district of Tamil Nadu through the application of geospatial techniques (GIS). By leveraging such advanced methodologies, this study provides valuable data that enhances the understanding of shoreline dynamics, thereby supporting more informed decisions in the management and conservation of coastal resources.

The in-depth analysis[76] of shoreline evolution due to natural forces and human interventions in the coastal area of Visakhapatnam district. The study spans from 1989 to 2015, with satellite images and topographic maps captured at intervals of approximately five to ten years, facilitating a comprehensive assessment of erosion and accretion patterns. High-resolution satellite images were meticulously analyzed, employing imagery from Landsat 5 (1989), IRS-P6 LISS III (1999, 2005, 2010), LISS IV (2012), and Landsat 8 (2015). The analysis of these images was conducted using the Digital Shoreline Analysis System (DSAS), which enabled the precise detection of shoreline changes. To quantify these changes, two statistical methods were utilized: Linear Regression Rate (LRR) and End Point Rate (EPR). The EPR specifically was calculated by dividing the total distance of shoreline displacement by the time elapsed between the earliest and most recent images for each transect. The study encompasses a 135 km stretch of coastline, resulting in coastal maps that illustrate significant geomorphologic changes and shifts in shoreline position. The analysis revealed that approximately 74.6 km of the coastline is undergoing accretion at an average rate of +1.08 meters per year. Conversely, around 38.4 km of the coastline is experiencing erosion at an average rate of -1.40 meters per year, while 41.4 km remains stable. The findings underscore the utility of integrating satellite imagery with robust statistical

methods like linear regression to analyze shoreline changes. The approach proves crucial for monitoring erosion and informing preventative strategies, thereby contributing to the sustainable management of coastal resources and supporting economic development in coastal regions.

The study[77], investigates the variability of shoreline changes, which are influenced by both human activities and sea level rise, utilizing advanced remote sensing and digital image processing techniques to enhance the accuracy and efficiency of demarcation. The primary objectives of the research were to extract shoreline data using the Sobel edge detection operator and visual interpretation techniques, and to analyze these changes using the Vector Overlay Technique (VOT) and statistical methods over a 35-year period from 1978 to 2013. Quantitatively, the study determined that 2.41 square kilometers of the area were impacted by shoreline transgression, while 7.64 square kilometers were affected by regression. Qualitatively, the analysis of shoreline change rates revealed a range from 10.72 meters of regression to -7.35 meters of transgression. The measurements are crucial for predicting potential risk areas and identifying zones under threat within the study area. The combined use of edge detection for precise shoreline extraction and vector overlay for detailed change analysis provides a robust framework for understanding the dynamics of coastal environments. The approach not only facilitates a more accurate assessment of spatial and temporal variations in the shoreline but also enhances the capability for monitoring at-risk areas, thereby supporting more informed coastal management and mitigation strategies.

Chapter 3

Databases And Methodology:

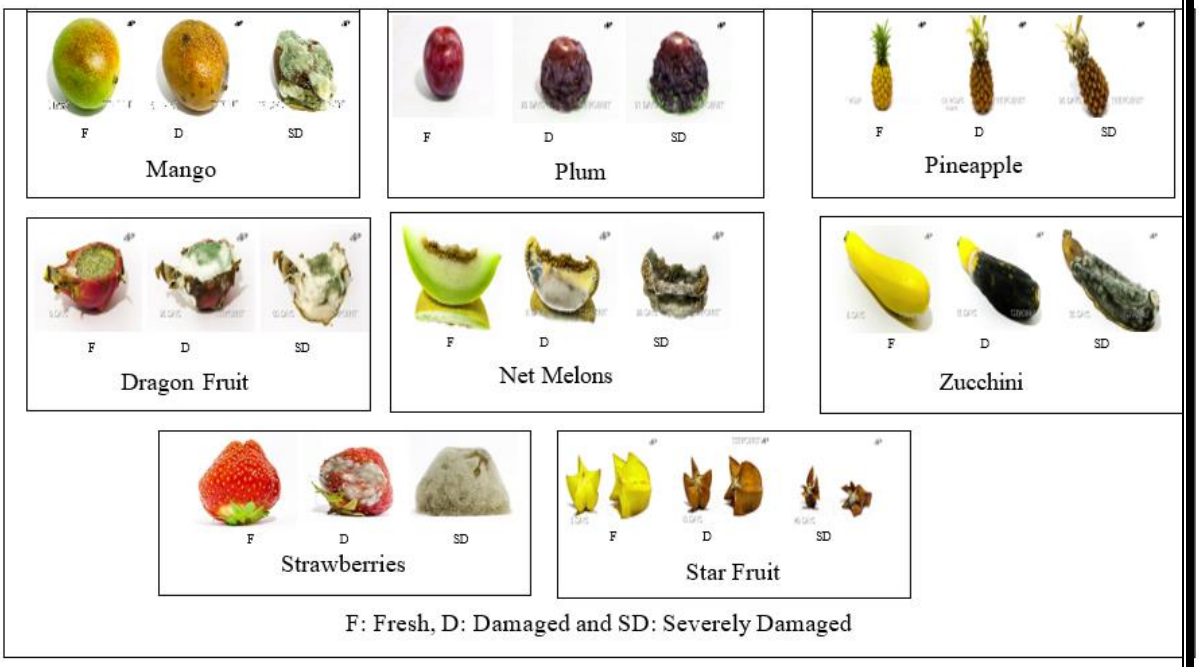
3.1 EXPLANATORY ANALYSIS OF FRUITYHUB DATABASE:

FruityHub, the novel database introduced in this study, comprises a total of 1,786 image frames spanning eight distinct fruit categories: Dragon Fruit, Net Melons, Strawberries, Star Fruit, Zucchini, Mango, Pineapple, and Plum. This database categorizes each fruit image under one of three classifications- Fresh, Damaged, and Severely Damaged facilitating the training of automated systems for edibility assessment. The collection features images that represent various levels of fruit freshness, sourced from publicly accessible platforms, with corresponding links provided in Table II. Visual examples of each fruit category across the three classes are illustrated in Figure 1, while Figures 2 and 3 depict the intra-category and inter-category variations in the dataset through graphical representations.

TABLE II. VIDEOS FROM WHICH IMAGE FRAMES ARE EXTRACTED TO CREATE FRUITYHUB DATABASE

Fruits	Video Duration	Download Link
Mango	5.27 secs	https://www.youtube.com/watch?v=NzAYAcneGmY
Dragon Fruit	3.19 secs	https://www.youtube.com/watch?v=dJp427CzSh4
Star Fruit	3.39 secs	https://www.youtube.com/watch?v=SRVwxUW5dwM
Strawberries	2.26 secs	https://www.youtube.com/watch?v=1Z4_hWVOA1Q
Net Melons	2.17 secs	https://www.youtube.com/watch?v=1DxH3mQAGPI
PineApple	4.15 secs	https://www.youtube.com/watch?v=bRrp-ZrJifA
Plum	4.26 secs	https://www.youtube.com/watch?v=HtEQKeoSsUM

Fig1. Examples of images included for each class corresponding to each fruit category in FruityHub database



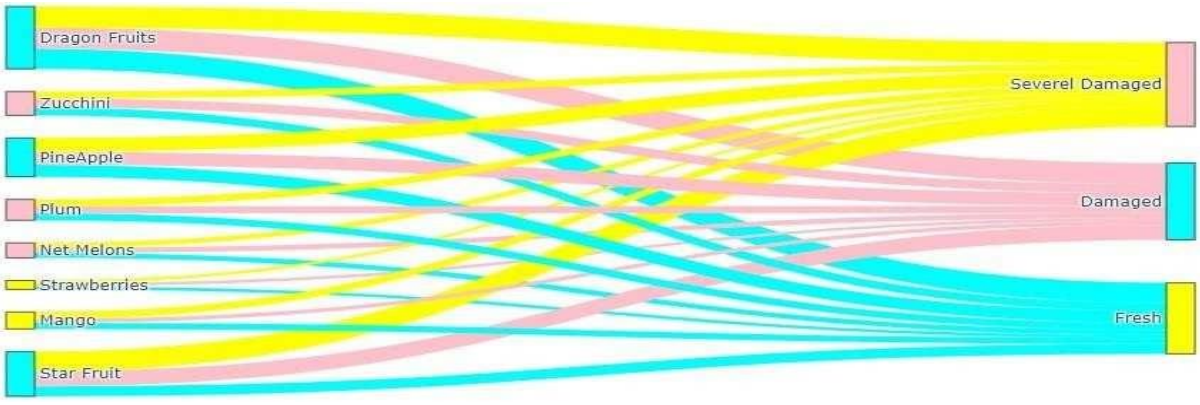
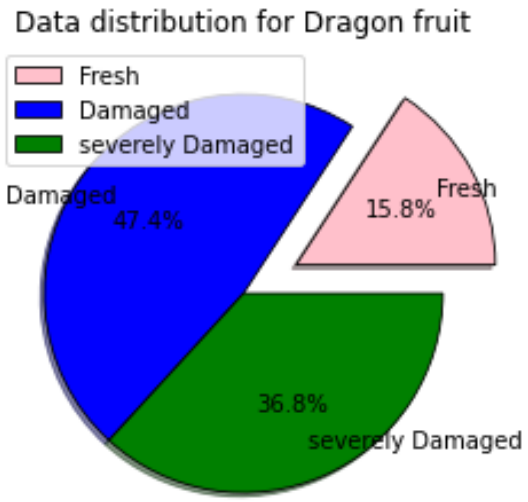
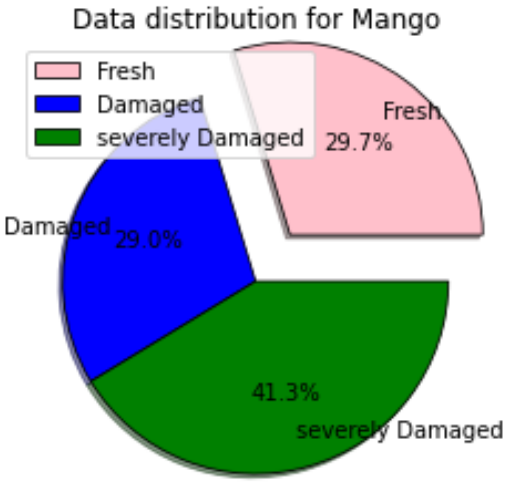
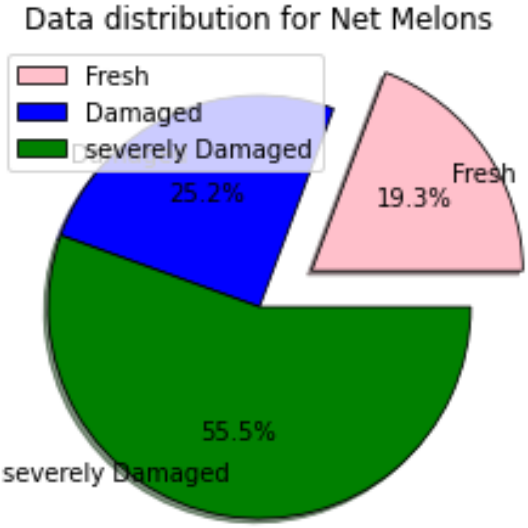
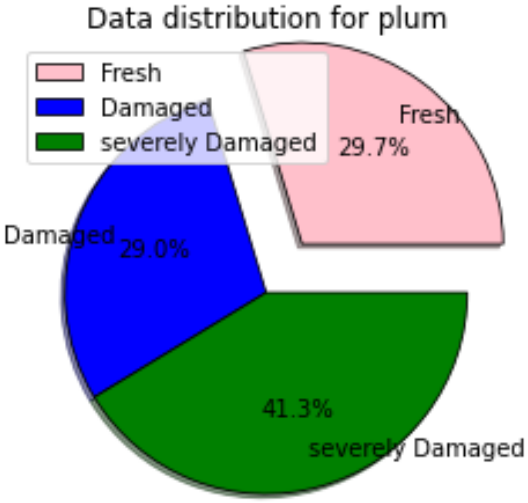


Fig 2. Alluvial Flow Diagram representing inter-class as well as intra-class data distribution


Data distribution for Dragon fruit
Fresh
Damaged
severely Damaged
Damaged
47.4%
15.8%
Fresh
36.8%
severely Damaged


Data distribution for Mango
Fresh
Damaged
severely Damaged
Fresh
29.7%
Damaged
29.0%
41.3%
severely Damaged


Data distribution for Net Melons
Fresh
Damaged
severely Damaged
25.2%
Fresh
19.3%
55.5%
severely Damaged


Data distribution for plum
Fresh
Damaged
severely Damaged
Fresh
29.7%
Damaged
29.0%
41.3%
severely Damaged

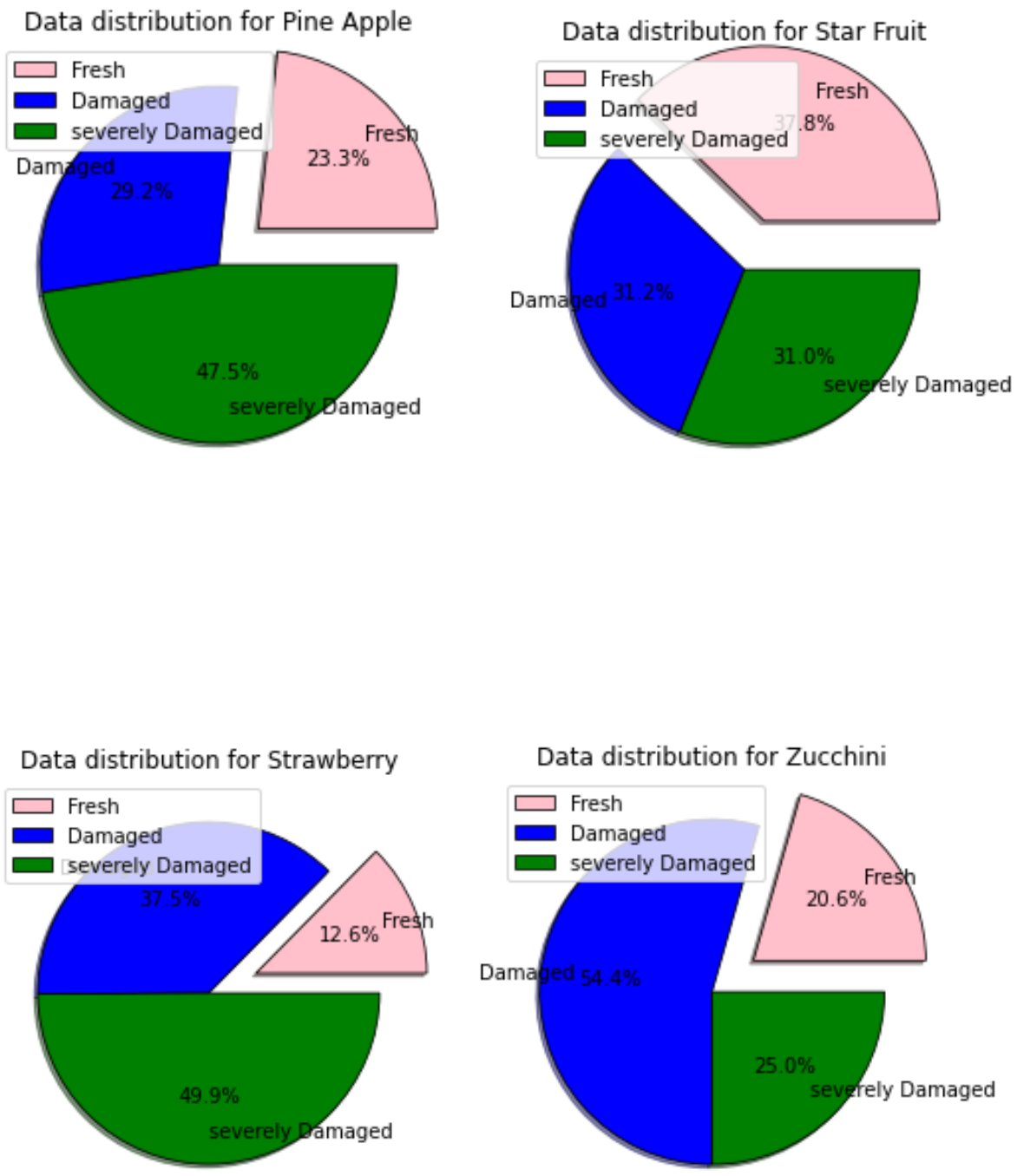


Fig 3. Inter-class data distribution corresponding to each fruit category

The architectures of deep neural networks which are used for performing the real life effectiveness of the newly curated fruityHub , GreemMedNet database are explained in details in section 2.1 and 2.2 in chapter 2.

3.2 Nature's Diabetes Helpers: Insulin Leaves Repository:

TABLE III: EXAMPLES OF HEALTHY AND DISEASED LEAF IMAGES INCLUDED IN NATURE'S DIABETES HELPERS: INSULIN LEAVES REPOSITORY DATABASE

Healthy Insulin Leaves						
Damaged Insulin Leaves						

This specialized database comprises 600 images of insulin leaves, evenly distributed between healthy and damaged classification, with 300 images per category. This balanced dataset represents a significant advancement in the field, emphasizing the medicinal properties of the insulin leaves, including their hypoglycemic, antioxidant, and anti-inflammatory capabilities. These attributes are crucial in Ayurvedic medicine, underscoring the leaves' therapeutic potential beyond conventional botanical image databases. The dataset is particularly designed to facilitate the training of deep neural networks for the automatic classification of the leaves as either diseased or healthy. To enhance the robustness of the training process, the images feature complex backgrounds incorporating elements such as soil, weeds, and other plant fragments. Additionally, the images are captured under various lighting conditions, further enriching the dataset. This diversity is critical for developing algorithms capable of accurate real-world recognition and classification tasks, thereby supporting advanced research and applications in diabetes management through the use of medicinal plants.

The images within the Nature's Diabetes Helpers: Insulin Leaves Repository were acquired using advanced mobile phone cameras, specifically the Samsung Galaxy S20 FE 5G and the Redmi Note 9 Pro Max. The Samsung Galaxy S20 FE 5G is equipped with a sophisticated camera system featuring a 12MP Dual Pixel OIS (Optical Image Stabilization) F1.8 wide rear camera, an 8MP OIS telephoto camera, and a 12MP ultra-wide camera with 30X Space Zoom capabilities. In contrast, the Redmi Note 9 Pro Max incorporates a multi-lens array consisting of a 64MP primary sensor complemented by 8MP, 5MP, and 2MP secondary sensors, all enhanced by Artificial Intelligence (AI) technology for optimized image capture. This dataset includes visual samples of both healthy and diseased insulin leaves, providing valuable visual data for training and

research purposes. The examples of these leaf conditions are systematically catalogued in Table III , presenting a clear and detailed reference for users and researchers engaging with the database.

3.2.1 GreenMedNet: Advanced Hyperparameter-Optimized Attention-Based Neural Architecture

GreenMedNet is an innovative neural architecture that emphasizes hyperparameter optimization to achieve significant improvements in computational efficiency and model compactness. This architecture employs Depth-wise Separable Convolutional layers and Global Average Pooling 2D (GlobalAveragePooling2D) layers to substantially decrease the total parameter count, thus enhancing processing speed and network efficiency. Depth-wise Separable Convolutional layers in GreenMedNet include both depth-wise and point-wise convolutions, functioning as bottlenecks that streamline feature map extraction. This design is inherently more parameter-efficient than traditional convolutional layers, as it separates the filtering and combining steps, reducing the computational burden and parameter size. The adoption of GlobalAveragePooling2D layers over traditional Flatten layers further reduces parameter counts by summarizing spatial information across activation maps efficiently. Each feature map channel is condensed into a single representative value, which simplifies the output dimensionality and supports a more compact model structure. Additionally, GreenMedNet integrates Batch Normalization layers to expedite model convergence by mitigating internal covariate shift during training. The architecture also incorporates Dropout layers to prevent overfitting, thereby enhancing the generalizability of the model across diverse datasets. These features collectively contribute to a robust, efficient, and high-performing neural network tailored for medical applications.

3.2.2 Methodology:

Hyperparameter Optimized GreenMedNet Architecture

The GreenMedNet architecture underwent meticulous hyperparameter optimization using the Random Search method. This optimization process targeted various architectural parameters including the number of Depth-wise Separable Convolutional layers, neuron count in Dense Layers (D1 and D2), dropout rates in these layers (Dp1 and Dp2), and the reduction ratio in the spatial attention block.

The initial hyperparameter search space was defined as follows:

- Depth-wise Separable Convolutional layers: 3 to 5 layers
- Reduction ratio in the spatial attention block: between 8 and 12
- Neurons in Dense Layer D1: 64, 128, or 256
- Neurons in Dense Layer D2: 32, 64, or 128
- Dropout values for Dp1 and Dp2: ranging from 0.3 to 0.5

The optimal configuration identified through Random Search included two Depth-wise Separable Convolutional layers, a reduction ratio of 8, 256 neurons in D1, 128 neurons in D2, with dropout rates of 0.4 and 0.5 for Dp1 and Dp2 respectively. This architecture was chosen based on its superior validation accuracy. For loss computation, Categorical Cross Entropy was employed alongside the Adam optimizer, which was configured with momentum parameters $\beta 1=0.92$ and $\beta 2=0.98$.

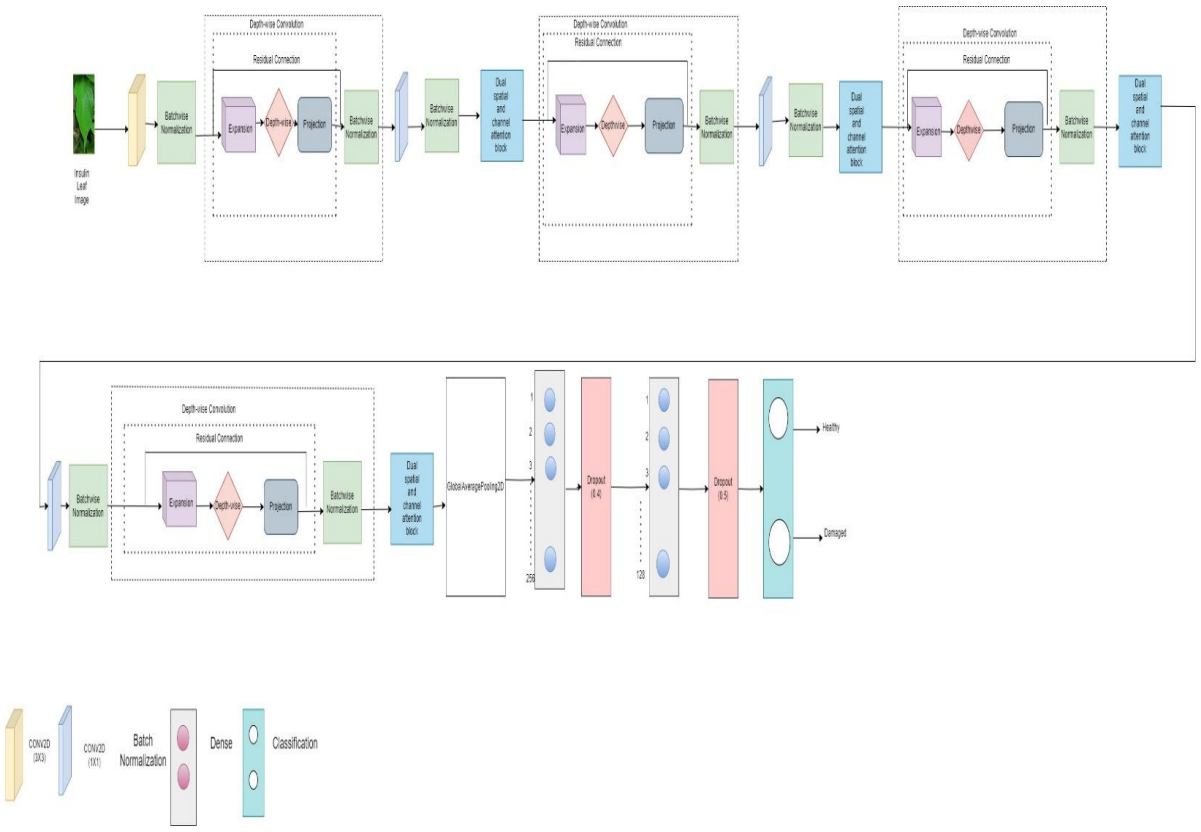


Fig 4: Pictorial representation of detailed architecture of GreenMedNet (please zoom in for better view)

The choice of Exponential Rectified Linear Unit (EReLU) for intermediate layer activations addresses common neural network issues such as vanishing gradients and the dying ReLU problem. The softmax function was used in the final classification layer to facilitate effective multiclass classification. Additionally, L2 regularization was applied in both Convolutional and Dense layers to combat overfitting. Visual representations of the GreenMedNet architecture and the detailed configuration of the Dual spatial and channel attention block are provided in Figures 4 and 5, respectively, offering insights into the structural and functional aspects of the network.

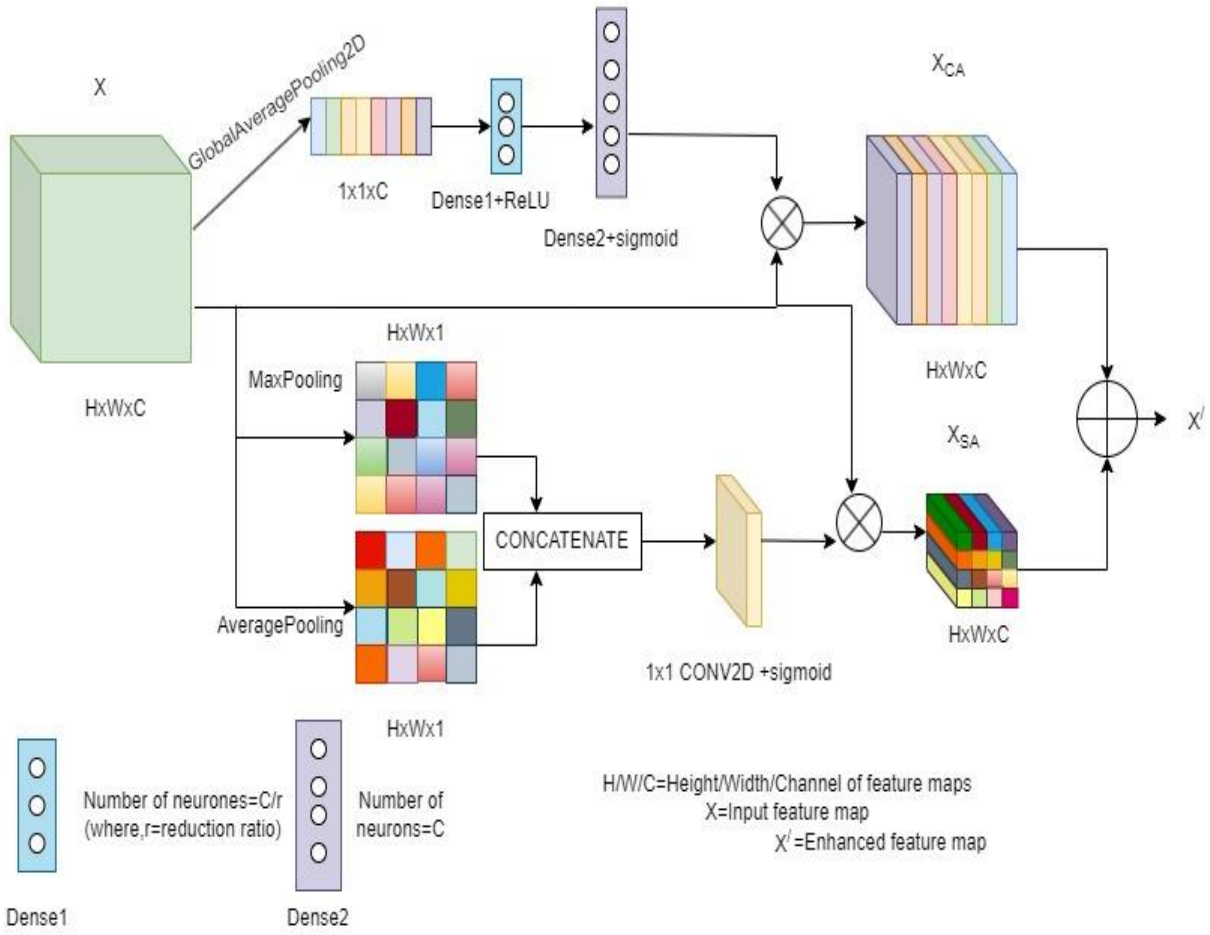


Fig 5: Detailed overview of the Dual spatial and channel attention block

3.3 Nature's Best vs. Bruised: A Veggie Evaluation

3.3.1 Specification Table IV:

Subject	Smart Agriculture, Vegetable freshness evaluation, Deep Neural Networks
Specific Subject area	Automated Vegetable freshness quality evaluation
Data type	Images of vegetables from Fresh to Damaged to Severely Damaged
Data acquisition	Images of vegetables included in this dataset are acquired using varied camera angles, non-uniform illumination and consistent white background.
Data format	Raw
Dataset preparation	Various freshness stages of vegetables were captured using the high-resolution rear cameras of three different mobile phones. These images were saved in JPG format after resizing to a fixed dimension of 256 × 256 using a Python script. The resized images were organized into six folders: Cowpea, Snake Gourd, Spiny Gourd, Ivy Gourd, Taro root and Turmeric. Within these folders, the vegetable images were further categorized into six subfolders based on their freshness level: Fresh, Damaged, and Severely Damaged. All images were captured under different lighting conditions against a white background. This meticulously curated vegetable image dataset serves a vital purpose in the testing, training, and validation of automated models designed for evaluation of freshness levels of vegetables. Researchers and developers can utilize this dataset to enhance the accuracy and efficiency of their vegetable-related projects, benefiting from the diverse quality and type variations captured in the images.
Data source location	This dataset is prepared at Jadavpur University, Kolkata, India. $22.4989^{\circ}N, 88.3714^{\circ}E$
Data accessibility	Repository name: Nature's Best vs. Bruised: A Veggie Evaluation Data Identification Number (doi): Direct URL to data:

3.3.2 Value of Data

- This database contains a total of **4464** high-quality images of six different types of vegetables namely, Cowpea, Snake Gourd, Spiny Gourd, Ivy Gourd, Taro root and Turmeric.
- Images included within each vegetable category are further categorized into three classes namely, Fresh, Damaged, and Severely Damaged.
- The provided dataset offers a valuable resource for researchers working on deep learning solutions focused on classifying vegetables according to their freshness levels.
- The dataset holds immense potential in the development of high-quality vegetable freshness evaluation applications.

3.3.3 Data description

The research has pioneered the creation of a unique database named " Nature's Best vs. Bruised: A Veggie Evaluation," featuring **4464** images representing six commonly consumed vegetables in India: Cowpea (Scientific name: Vigna sinensis Savi), Snake Gourd (Scientific name: Trichosanthes cucumerina), Spiny Gourd (Scientific name: Momordica dioica), Ivy Gourd (Scientific name: Coccinia grandis), Taro root (Scientific name: Colocasia esculenta) and Turmeric (Scientific name: Curcuma longa). These specific vegetables were chosen due to their widespread consumption and affordability, particularly in rural areas, and notably, they were absent from existing databases.

The images within my database authentically capture the natural progression of these vegetables, showcasing their transition from Fresh state to Damaged to Severely Damaged conditions, without any external manipulation. I have classified these images into three distinct categories: Fresh, Damaged, and Severely Damaged. To ensure diversity, the photographs were captured utilizing varied camera angles, non-uniform illumination conditions and consistent white background.

This comprehensive database stands as a valuable resource for researchers in the field, addressing the crucial need for robust datasets and facilitating advancements in automated vegetable quality assessment techniques.

Example 25: Examples of images included in this newly curated database are given below:

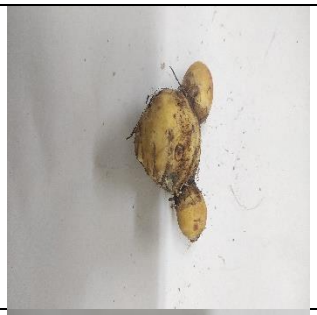
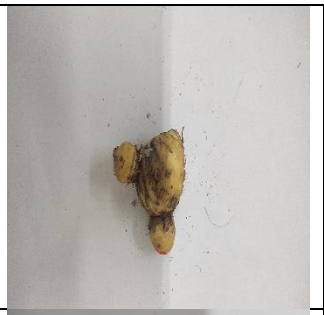
Turmeric

Fresh				
Damaged				
Severely Damaged				

Spiny gourd:

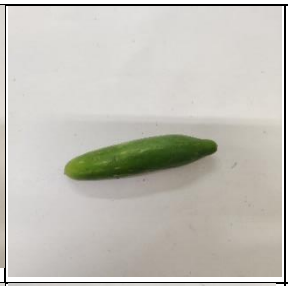
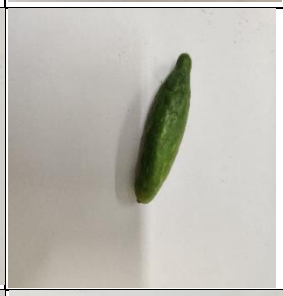
Fresh				
Damaged				
Severely Damaged				

Taro Root

Fresh				
Damaged				

Severely Damaged			

Cocinia

Fresh				
Damaged				
Severely Damaged				

Snake Gourd

Fresh		
Damaged		
Severely Damaged		

Cowpea

Fresh		
Severely Damaged		

3.3.4 Experimental Design, Materials and Methods

The high-definition rear cameras of OnePlus7T, Redmi Note 9 pro max and OnePlus Nord mobile phones were employed to capture the photographs of the vegetables. After capturing the images, they are resized to a fixed dimension of 256x256 using a python script and are stored in appropriate folders in .jpeg format.

3.3.5 Materials or Specification of Image Acquisition System

OnePlus7T camera specifications: 48 MP Ultra-wide Triple camera
Redmi Note 9 pro max camera specifications: AI Quad camera array 64 MP+8 MP+5MP+2MP
OnePlus Nord camera specifications: 48 OIS+8+5+2 MP Quad Camera, 32+8 MP Dual Front Camera

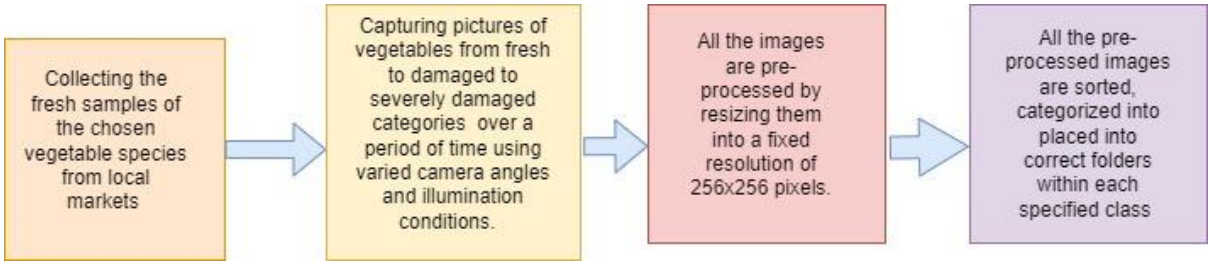


Fig.6: Steps adapted to curate the Nature's Best vs. Bruised: A Veggie Evaluation dataset

Table V

3.3.6 Specification of image acquisition devices:

Sl. No	Properties	Camera 1	Camera 2	Camera 3
1	Device name	OnePlus7T	Redmi Note 9 pro max	OnePlus Nord
2	Camera specifications	**Rear camera** 48 megapixel (f/1.6,0.8 micron) +16 megapixel(f/2.2) +12 megapixel (f/2.2) **Front camera** 16 megapixel (f/2.0,1.0 micron)	**Quad camera** 64 megapixel (f/1.9, 0.8 micron) +8 megapixel (f/2.2)+5 megapixel (f/2.4)+2 megapixel (f/2.4)	**Quad camera** 48 megapixel (f/1.8, 0.8 micron) +5 megapixel (f/2.3)+5 megapixel (f/2.4)+2 megapixel (f/2.4)

Table VI : Specification of Image details And Quality

Sl.No.	Image details	Image quality
1	Dimension	256x256 pixels
2	Height	256
3	Width	256
4	Vertical resolution	72 dpi
5	Horizontal resolution	72 dpi
6	Bit depth	24
7	Resolution unit	2
8	Colour representation	sRGB

Table VII

3.3.7 Nature's Best vs. Bruised: A Veggie Evaluation: Dataset details

Classes	Vegetable Species	Camera angles, illumination and image background specifications	Number of images included under each class for each vegetable species
Fresh Damaged Severely Damaged	**Cowpea** (Scientific name: Vigna sinensis Savi), **Snake Gourd** (Scientific name: Trichosanthes cucumerina), **Spiny Gourd** (Scientific name: Momordica dioica), **Ivy Gourd** (Scientific name: Coccinia grandis), **Taro root** (Scientific name: Colocasia esculenta) and **Turmeric** (Scientific name: Curcuma longa)	Images are captured using varied camera angles, non-uniform illumination conditions in the presence of artificial light and using consistent white background, thereby ensuring the diversity in samples.	**Fresh** Cowpea: 203 Snake Gourd: 122 Spiny Gourd: 418 Ivy Gourd: 246 Taro root: 228 Turmeric: 350 **Damaged** Cowpea: Nil Snake Gourd: 124 Spiny Gourd: 487 Ivy Gourd: 254 Taro root: 186 Turmeric: 335 **Severely Damaged** Cowpea: 204 Snake Gourd: 123 Spiny Gourd: 420 Ivy Gourd: 254 Taro root: 186 Turmeric: 324

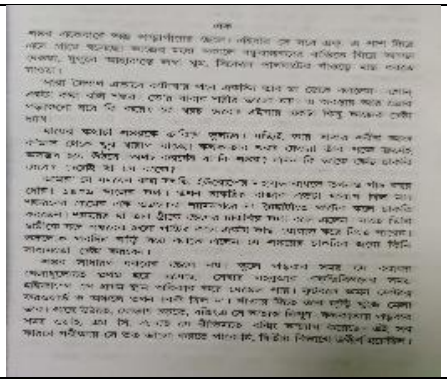
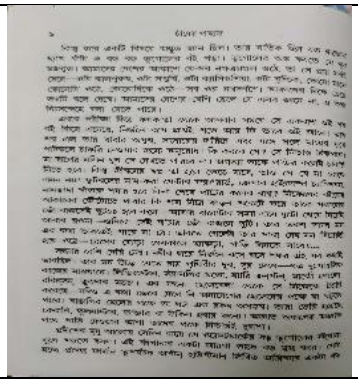
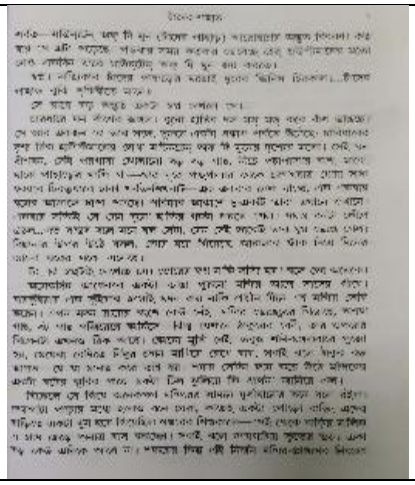
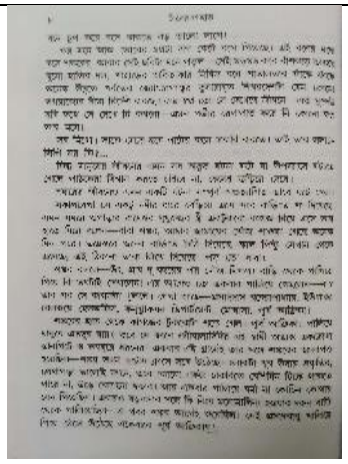
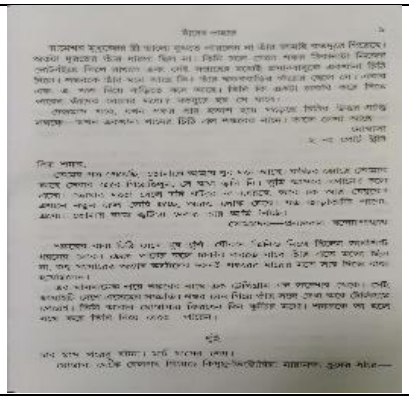
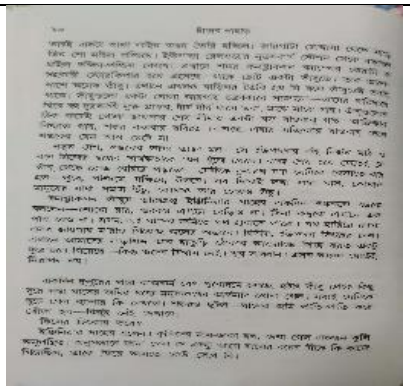
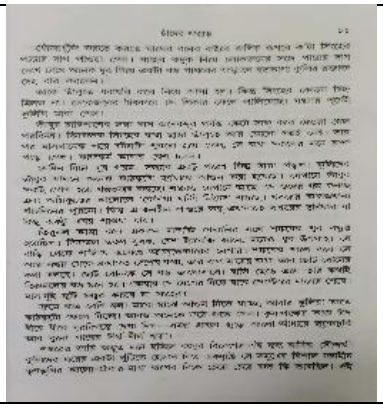
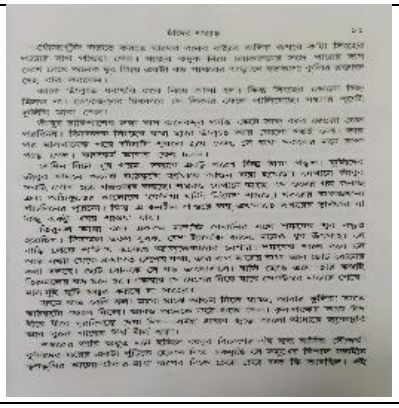
3.3.8 Methodology:

For the development of this database, all vegetable species were initially acquired in fresh condition from local markets. These samples were then systematically transitioned through three stages of condition—Fresh, Damaged, and Severely Damaged—under controlled laboratory settings to ensure consistent sample transformation. The imaging process involved capturing photographs from various angles and under non-uniform lighting conditions to simulate real-world scenarios, while maintaining a consistent white background to standardize image analysis. The images for each category and class of vegetable were captured and subsequently resized to a uniform resolution of 256x256 pixels. These standardized images were then organized into appropriately labelled folders corresponding to each vegetable type and condition stage. This methodical categorization and standardization facilitate the effective use of the database for training, validating, and testing automated systems designed for the assessment of vegetable freshness. The comprehensive and varied dataset enhances the real-life applicability of the database, making it a robust resource for developing and fine-tuning algorithms aimed at automating the evaluation of vegetable freshness. This approach not only supports the accuracy of the models developed but also improves their generalizability and effectiveness in practical applications.

3.4 BengaliprintDB: A Repository of Machine-Printed Bengali Documents

3.4.1 Database:

To address the gap in available resources for Optical Character Recognition (OCR) technology, particularly in the interpretation of Bengali text, I have introduced a new dataset, BengaliPrintDB. This dataset is critical for enhancing the classification capabilities of OCR systems to distinguish between handwritten and machine-printed documents. Current resources predominantly consist of handwritten Bengali words, documents, characters, and digits. However, the categorization of documents as handwritten or machine-printed is essential for reliable text recognition and conversion into machine-readable formats.

Im1	Im2
	
Im3	Im4
	
Im5	Im6
	
Im7	Im8
	

Example 26: BengaliprintDB Dataset

3.4.2 Methodology:

The BengaliPrintDB is a meticulously curated dataset comprising 450 images of machine-printed Bengali text at the document level. These images have been selectively sourced from a variety of publications authored by esteemed Bengali writers, ensuring a rich diversity in content. The dataset features a balanced collection of texts from both historical and contemporary works, thereby encompassing a broad spectrum of image qualities and typographic styles. This diversity is critical for training robust OCR systems capable of performing across different qualities and ages of printed materials.

This dataset not only fills a significant void in the availability of machine-printed Bengali text resources but also provides a foundational platform for further research and development in document analysis and linguistic recognition technologies. By facilitating more accurate and efficient document classification, BengaliPrintDB aims to significantly enhance the performance of OCR applications dealing with Bengali texts.

3.4.3 Conclusion:

In summary, the distinction between handwritten and machine-printed documents in OCR applications is not merely a technical challenge but a fundamental requirement for enhancing the accuracy and efficiency of OCR systems. By implementing advanced machine learning and deep learning techniques tailored to the unique characteristics of each document type, this research has pioneered a methodical approach to OCR that significantly boosts the effectiveness of digitizing documents. The development of specialized algorithms for different text types, coupled with adaptive preprocessing and feature extraction strategies, ensures that the OCR technology can meet the diverse needs of modern digital document management. Furthermore, the use of dedicated databases for training these models underlines the importance of specialized resources in achieving high OCR performance. This work lays a robust foundation for future innovations in OCR technology, facilitating more accessible, efficient, and accurate digital data conversion across various sectors, ultimately driving forward the digital transformation agenda in multiple industries.

3.5 In-depth survey of automated shoreline alteration identification methods

3.5.1 Common datatype used for performing automated shoreline change detection:

Landsat: The Landsat program, initiated with the launch of Landsat 1 in 1972, represents a foundational element in the domain of Earth observation, providing nearly five decades of consistent data. This extensive dataset is invaluable for analyzing long-term environmental trends and changes on Earth's surface. One of the program's primary strengths is its comprehensive global coverage, which enables a detailed understanding of regional and global-scale environmental processes. Such coverage is indispensable for both researchers and policymakers engaged in environmental management and planning.

Additionally, the multispectral imaging capability of Landsat satellites is a critical feature. The satellites are equipped to capture data across multiple spectral bands, significantly enhancing the precision of land cover classification. This capability is pivotal for monitoring vegetation health, differentiating between various types of land covers, and identifying natural resources. The evolution of sensor technology in the Landsat program has substantially augmented its utility and application. Early satellites, Landsat 1 through 5, were outfitted with the Multispectral Scanner (MSS) sensor, which captured data in four spectral bands. This setup evolved with Landsat 4 and 5, which incorporated the Thematic Mapper (TM) sensor, expanding the range to seven spectral bands and improving overall spectral sensitivity. Further advancements were seen with Landsat 7's Enhanced Thematic Mapper Plus (ETM+), which maintained the seven-band system but introduced enhanced capabilities in thermal infrared and spatial resolution, including a panchromatic band. Continuing this trajectory of innovation, Landsat 8 features the Operational Land Imager (OLI) and Thermal Infrared Sensor (TIRS), with the former offering nine spectral bands for more detailed observations and the latter enhancing thermal data sensitivity.These technological enhancements have continuously improved the quality and comprehensiveness of data provided by the Landsat program, supporting a wide array of applications in Earth science and environmental monitoring. Evolution of Landsat over the years is pictorially represented in Fig 6.

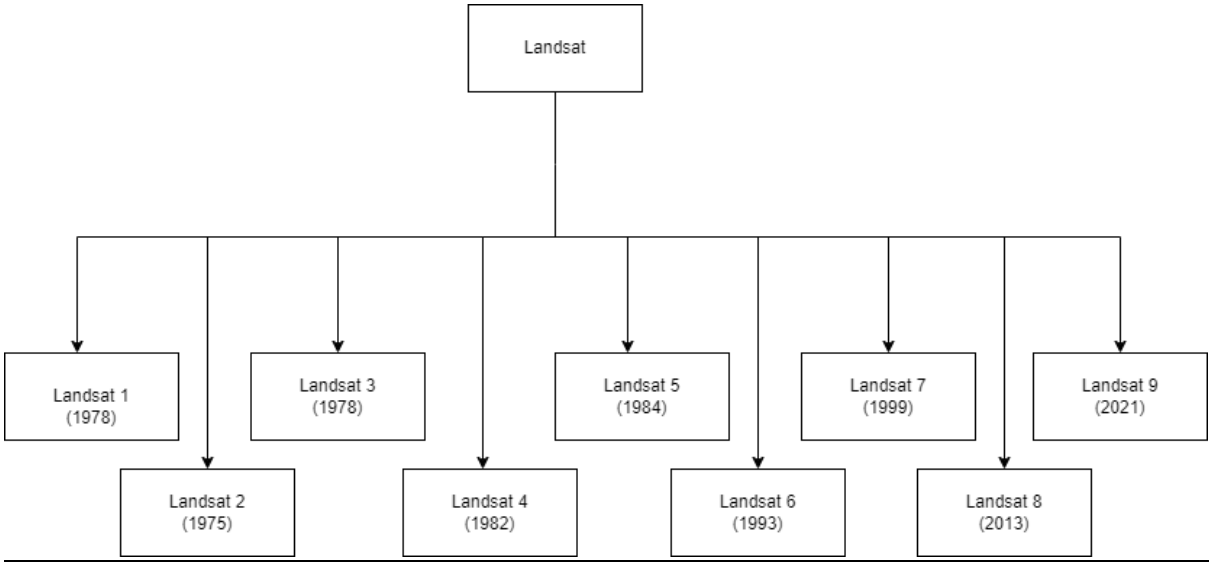


Fig 6: Evolution of Landsat over the years

Liss: The Linear Imaging Self-Scanning Sensor (LISS) series, a pivotal component of the Indian Remote Sensing (IRS) satellite program managed by the Indian Space Research Organisation (ISRO), has exhibited significant advancements since its inception. The evolution of the LISS sensors illustrates the progression in remote sensing capabilities, enhancing the scope and precision of environmental and land use monitoring. Initiated with LISS-1 on the IRS-1A satellite in 1988, the series began with a single spectral band designed primarily for regional studies. This foundational sensor was soon complemented by LISS-2, which featured four spectral bands, thus broadening its utility in agricultural assessments and land cover mapping. The subsequent iteration, LISS-3, deployed on IRS-1B, improved upon its predecessors by offering three spectral bands, thereby providing enhanced data for crop monitoring and natural resource management. A significant enhancement came with the introduction of LISS-4 on the IRS-P6 (Resourcesat-1) satellite in 2003. This variant included multispectral capabilities tailored for detailed analyses in agriculture, forestry, and urban planning. Concurrently, the LISS-4T model incorporated thermal infrared technology, facilitating applications in thermal mapping and expanding the sensor's utility. Further advancements were realized with enhanced versions of LISS-3 on subsequent satellites, which retained the original band configurations but offered superior radiometric and spatial resolutions. The advanced LISS-3 on Resourcesat-2B notably improved both spatial resolution and radiometric quality, significantly refining data precision.Throughout its operational history, LISS technology has supported a wide range of applications, including agriculture, disaster management, and environmental monitoring. The continual improvements in LISS sensors have not only ensured consistent data continuity but have also enhanced the capacity for conducting longitudinal studies of environmental changes.

These technological advancements have substantially augmented India's capabilities in remote sensing, thereby contributing to more informed decision-making and policy development. Despite facing challenges related to spectral and spatial limitations, the ongoing evolution of the LISS series remains crucial in meeting the diverse remote sensing needs of India. The evolutionary journey of LISS over the years is visually depicted in Fig.7

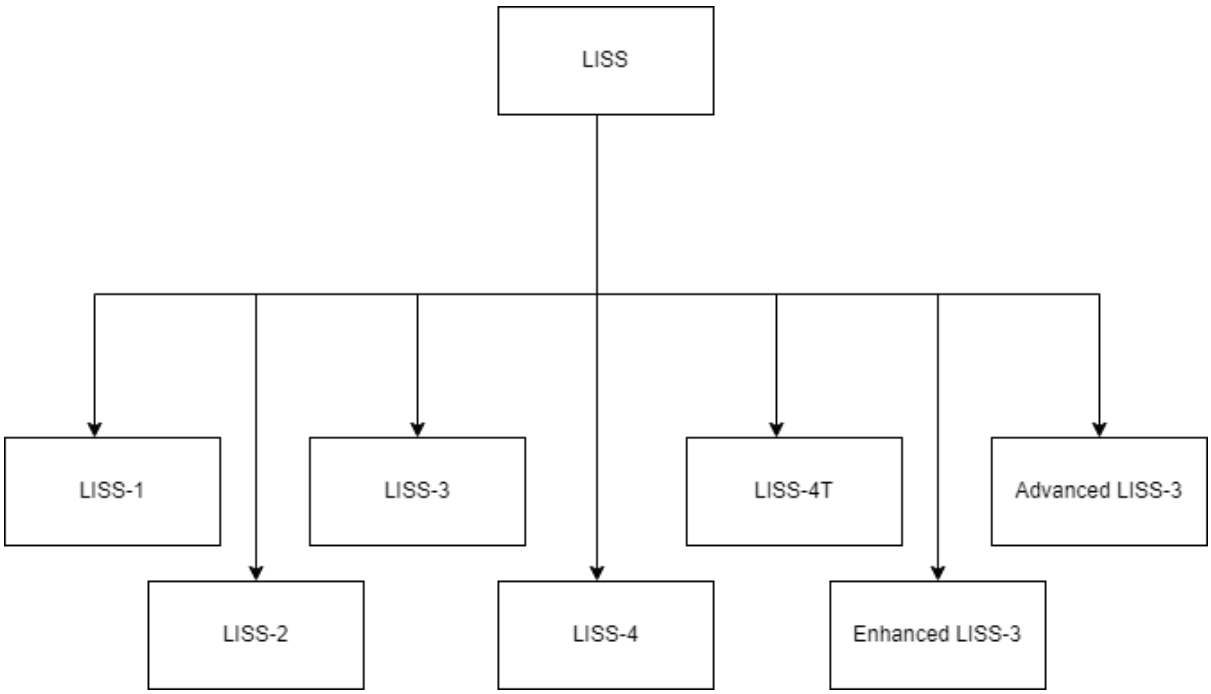


Fig 7: Evolutionary journey of LISS over the years

WorldView: The WorldView satellite series, initiated in 2007, represents a significant technological progression in Earth observation capabilities. The series began with WorldView-1, which offered high-resolution panchromatic imagery at 0.5-meter resolution, a breakthrough that significantly enhanced precise mapping and disaster assessment capabilities. Following WorldView-1, the launch of WorldView-2 in 2009 marked a substantial advancement in the satellite's imaging capabilities. It featured eight multispectral bands with a resolution of 1.85 meters, including the red edge bands, which are crucial for improving land cover classification and supporting advanced remote sensing applications. The evolution continued with WorldView-3, launched in 2014, which significantly expanded the spectral tools available by including shortwave infrared (SWIR) bands in its multispectral suite. These SWIR bands are particularly effective for distinguishing between different materials, making WorldView-3 a powerful tool for more complex environmental and geological studies. WorldView-4, introduced in 2016, maintained the enhanced spectral capabilities and resolutions established by its predecessor, contributing to greater data availability and increasing the revisit frequency

of satellite imaging. This improvement has been vital in areas requiring frequent monitoring such as urban development and environmental change. Collectively, these advancements have significantly broadened the analytical capabilities of the WorldView sensors, providing high spatial resolution and extensive multispectral capacities. These features enable detailed imaging of fine details and small features on Earth's surface with remarkable precision. The inclusion of specialized spectral bands, such as red edge and SWIR, allows for detailed differentiation of surface materials and characteristics, supporting a wide range of applications from agriculture and disaster management to urban planning and mineral exploration. The commercial availability of WorldView

imagery further democratizes access to high-quality satellite data, allowing a diverse array of users to utilize this resource for varied applications, thus expanding the impact of WorldView technology across multiple fields. The progressive evolution of WorldView over time is artistically illustrated in Fig.8.

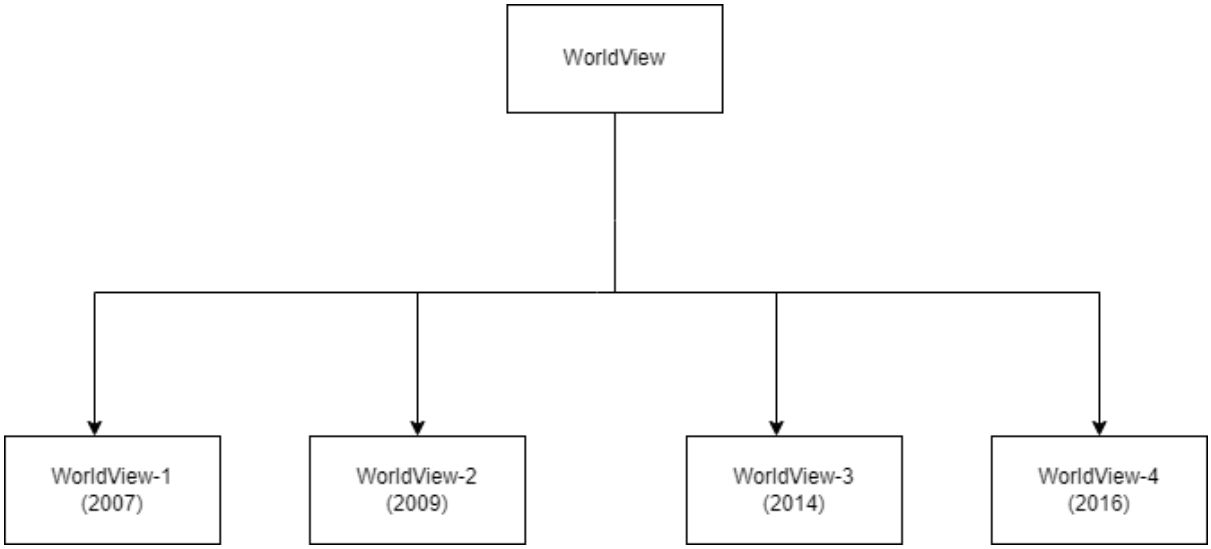


Fig.8 Progressive evolution of WorldView over time

QuickBird: QuickBird-1, launched on October 18, 2001, marked a significant advancement in satellite imaging technology with its high-resolution capabilities. It was equipped with a panchromatic sensor capable of delivering imagery at an impressive spatial resolution of 0.61 meters. Complementing this, its multispectral sensor featured four spectral bands—blue, green, red, and near-infrared—with each band capturing images at a spatial resolution of 2.44 meters. This sensor configuration has proven extremely valuable for a multitude of applications, including high-resolution mapping, urban planning, and disaster assessment. QuickBird-2, which was launched simultaneously with QuickBird-1, mirrored its predecessor in both sensor configuration and performance. It maintained the same high-resolution panchromatic sensor with a 0.61-meter resolution and a multispectral sensor with the same four bands at a 2.44-meter resolution. Over the years, QuickBird-2 has continued to provide exceptional quality satellite imagery, proving to be an indispensable asset for a variety of applications. Both QuickBird-1 and QuickBird-2 are distinguished by their advanced multispectral and panchromatic imaging capabilities. The high-resolution panchromatic imagery is particularly valuable for detecting fine details and small features on the Earth's surface, enhancing the precision of satellite-derived data. Meanwhile, the multispectral imagery broadens the scope of analysis by providing data across multiple spectral bands, facilitating detailed assessments in areas such as land cover classification, environmental monitoring, and urban planning. As these satellite technologies and data offerings

continue to evolve, it is crucial to access the latest information from reliable sources, such as Digital Globe's official website, to ensure that data usage is based on the most current and accurate information. The progression of Quickbird's evolution across time is graphically represented in Fig.9

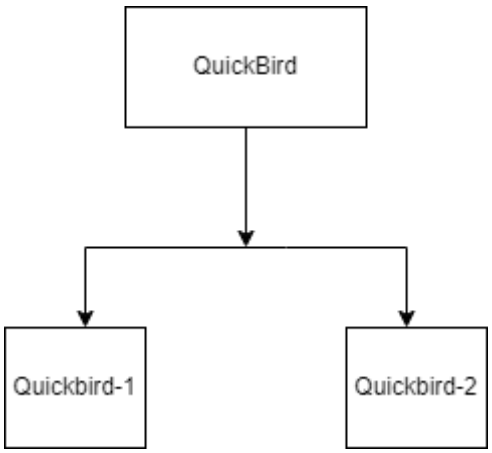


Fig.9 Progression of Quickbird's evolution across time

3.5.2 In-depth survey of automated shoreline alteration identification methods Results

This survey is designed to provide a thorough overview of the current state of research in shoreline change analysis, equipping researchers with a deep understanding of both foundational and emerging aspects in this field. The review meticulously addresses several critical dimensions:

Data Types and Quality Enhancements: I have examined the primary data modalities employed in shoreline change studies, focusing on how recent advancements in sensor technologies have improved the quality and accessibility of these data sets over time.

Predictive Techniques: An in-depth exploration of the diverse methodologies used for predicting shoreline changes is provided. This includes a detailed assessment of the techniques' theoretical underpinnings and their practical implementations in various studies.

Common Analysis Parameters: The review delineates the parameters commonly leveraged in shoreline change analyses. These include, but are not limited to, Normalized Difference Vegetation Index (NDVI), Endpoint Rate (EPR), Linear Regression Rate (LRR), New Water Surface Index (NWSI), and Shoreline Change Envelope (SCE).

Geographic Areas of Study: I have identified and discuss the geographic regions that have been the focus of shoreline change research, highlighting the specific types of data pertinent to these locales and the unique challenges they present.

Software Tools: Finally, the survey sheds light on the software tools that are integral to this field of study, including Digital Shoreline Analysis System (DSAS), Sentinel Application Platform (SNAP), and Quantum GIS (QGIS). These tools are essential for facilitating effective data analysis and interpretation in shoreline change research.

Overall, this survey aims to synthesize and present comprehensive insights into the methodologies, tools, and data involved in the study of shoreline dynamics, serving as a valuable resource for both novice and experienced researchers in the field.

3.5.3 Conclusion: This comprehensive survey seeks to equip researchers with an in-depth understanding of automated shoreline change detection while identifying potential areas for future inquiry. The future trajectory of this research includes enhancing the accuracy and resolution of detection algorithms, integrating data from multiple sources to provide a holistic view, and developing real-time monitoring systems. There is also a focus on advancing specialized machine learning techniques, quantifying uncertainties in predictive results, and conducting long-term analyses of shoreline changes. Furthermore, incorporating climate data is crucial for refining predictions in the context of global climate change. Engaging the public through crowdsourcing and citizen science, fostering interdisciplinary collaborations, and bridging the gap between research and policy implementation are essential. Addressing ethical concerns and promoting public awareness about sustainable coastal management are also pivotal. Effective collaboration among researchers, policymakers, and community stakeholders is indispensable for driving advancements in this dynamically evolving field.

Chapter 4

Discussion and Conclusion:

FruityHub: A diverse collection of fruits created foredibility estimation

4.1 COMPARATIVE ANALYSES' RESULTS OBTAINED USING FRUITYHUB DATABASE:

In this section, I have described the validation process used to evaluate the effectiveness of the newly developed FruityHub database, specifically designed for research in fruit edibility estimation. I have conducted a comprehensive performance analysis using fourteen prominent deep learning architectures: AlexNet, VGG16, ResNet152, MobileNetV2, ShuffleNetV2, SqueezeNet, InceptionV3, InceptionResNetV2, DenseNet121, NasNetLarge, NasNetMobile, GhostNetV2, EfficientNetB7, and Xception. These models were assessed based on their ability to accurately classify fruit images from the database. The evaluation involved a detailed comparative analysis using established quantitative metrics, including Test Accuracy, Precision, Recall, and F1 Score. Each metric provides critical insights into the models' classification performance, enabling us to discern not only the accuracy of each model but also their precision in identifying correct classifications, their recall ability to capture all relevant instances, and the F1 Score which balances the precision and recall metrics. This systematic approach ensures a robust validation of the FruityHub database's utility in supporting cutting-edge computational research in fruit edibility. The results are summarized in Table IX.

TABLE IX. COMPARATIVE ANALYSES' RESULTS

Parameters	AlexNet [12]								Vgg16 [13]							
	DF	NM	ST	SF	Z	M	PA	P	DF	NM	ST	SF	Z	M	PA	P
Test Accuracy (%)	0.63	0.97	0.97	0.94	0.88	0.67	0.91	0.93	0.63	0.55	0.50	0.94	0.68	0.84	0.48	0.41
Precision	0.40	0.97	0.97	0.94	0.92	0.55	0.91	0.93	0.40	0.31	0.25	0.94	0.84	0.87	0.23	0.17
Recall	0.63	0.97	0.97	0.94	0.88	0.67	0.91	0.93	0.63	0.56	0.50	0.94	0.68	0.84	0.48	0.41
F1 Score	0.49	0.97	0.97	0.94	0.88	0.59	0.91	0.93	0.49	0.40	0.33	0.94	0.62	0.81	0.31	0.24
Parameters	ResNet152 [14]								MobileNetv2 [15]							
	DF	NM	ST	SF	Z	M	PA	P	DF	NM	ST	SF	Z	M	PA	P
Test Accuracy (%)	0.95	0.94	0.96	0.87	0.95	0.62	0.93	0.85	0.91	0.97	0.98	0.82	0.99	0.92	0.95	0.94
Precision	0.95	0.95	0.96	0.89	0.95	0.56	0.94	0.86	0.91	0.97	0.98	0.83	0.99	0.92	0.95	0.94
Recall	0.95	0.94	0.96	0.87	0.95	0.62	0.93	0.85	0.91	0.97	0.98	0.82	0.99	0.92	0.95	0.94
F1 Score	0.95	0.94	0.96	0.87	0.95	0.56	0.93	0.84	0.91	0.97	0.98	0.82	0.99	0.92	0.95	0.94
Parameters	Inceptionv3 [16]								Xception [17]							
	DF	NM	ST	SF	Z	M	PA	P	DF	NM	ST	SF	Z	M	PA	P
Test Accuracy (%)	0.94		0.99	0.86	0.99	0.96	0.91	0.96	0.63	0.97	0.98	0.85	0.96	0.93	0.94	0.95
Precision	0.94		0.99	0.87	0.99	0.96	0.91	0.96	0.40	0.97	0.98	0.86	0.96	0.93	0.94	0.95
Recall	0.94		0.99	0.86	0.99	0.96	0.91	0.96	0.63	0.97	0.98	0.85	0.96	0.93	0.94	0.95
F1 Score	0.94		0.99	0.87	0.99	0.96	0.91	0.96	0.49	0.97	0.98	0.86	0.96	0.93	0.94	0.95
Parameters	ShuffleNetv2 [18]								SqueezeNet [19]							
	DF	NM	ST	SF	Z	M	PA	P	DF	NM	ST	SF	Z	M	PA	P
Test Accuracy (%)	0.63	0.55	0.5	0.39	0.54	0.5	0.29	0.29	0.63	0.81	0.38	0.65	0.67	0.78	0.48	0.69
Precision	0.40	0.31	0.25	0.15	0.30	0.25	0.09	0.08	0.40	0.86	0.14	0.59	0.59	0.69	0.23	0.81

Parameters	AlexNet [12]								Vgg16 [13]							
	DF	NM	ST	SF	Z	M	PA	P	DF	NM	ST	SF	Z	M	PA	P
Recall	0.63	0.55	0.5	0.39	0.54	0.33	0.29	0.29	0.63	0.81	0.38	0.65	0.67	0.78	0.48	0.69
F1 Score	0.49	0.40	0.33	0.22	0.38	0.5	0.13	0.13	0.49	0.78	0.21	0.61	0.62	0.71	0.31	0.62
Parameters	DenseNet121 [20]								InceptionResNetv2 [15]							
	DF	NM	ST	SF	Z	M	PA	P	DF	NM	ST	SF	Z	M	PA	P
Test Accuracy (%)	0.96	0.98	0.98	0.97	0.97	0.94	0.93	0.97	0.96	0.97	0.98	0.88	0.99	0.97	0.89	0.98
Precision	0.97	0.98	0.98	0.97	0.97	0.95	0.94	0.97	0.96	0.97	0.98	0.89	0.99	0.97	0.90	0.98
Recall	0.96	0.98	0.98	0.97	0.97	0.94	0.93	0.97	0.96	0.97	0.98	0.88	0.99	0.97	0.89	0.98
F1 Score	0.96	0.98	0.98	0.97	0.97	0.94	0.93	0.97	0.96	0.97	0.98	0.89	0.99	0.97	0.89	0.98
Parameters	NasNetLarge [22]								NasNetMobile [22]							
	DF	NM	ST	SF	Z	M	PA	P	DF	NM	ST	SF	Z	M	PA	P
Test Accuracy (%)	0.92	0.97	0.98	0.87	0.98	0.97	0.89	0.85	0.96	0.97	0.98	0.92	0.98	0.93	0.91	0.96
Precision	0.92	0.97	0.98	0.87	0.98	0.97	0.91	0.86	0.96	0.97	0.98	0.92	0.98	0.93	0.92	0.96
Recall	0.92	0.97	0.98	0.87	0.98	0.97	0.89	0.85	0.96	0.97	0.98	0.92	0.98	0.93	0.91	0.96
F1 Score	0.92	0.97	0.98	0.87	0.98	0.97	0.89	0.85	0.96	0.97	0.98	0.92	0.98	0.93	0.91	0.96
Parameters	EfficientNetB7 [23]								GhostNetv2 [24]							
	DF	NM	ST	SF	Z	M	PA	P	DF	NM	ST	SF	Z	M	PA	P
Test Accuracy (%)	0.63	0.55	0.5	0.51	0.54	0.50	0.48	0.41	0.63	0.55	0.5	0.39	0.54	0.42	0.53	0.41
Precision	0.40	0.31	0.25	0.28	0.30	0.25	0.23	0.17	0.40	0.31	0.25	0.15	0.30	0.21	0.25	0.17
Recall	0.63	0.55	0.5	0.5	0.54	0.50	0.48	0.41	0.63	0.55	0.5	0.39	0.54	0.42	0.41	0.41
F1 Score	0.49	0.40	0.33	0.31	0.38	0.33	0.31	0.24	0.49	0.40	0.33	0.22	0.38	0.29	0.30	0.24

4.1.1 Conclusion:

FruityHub represents a significant contribution to the field of fruit classification, comprising 1,786 images spanning fruit categories not previously included in existing databases, as detailed in Section II. This novel database has been rigorously validated through the application of several widely recognized deep neural networks, which have demonstrated strong classification performance for the specified fruit species. The encouraging results from this validation underscore the utility and relevance of FruityHub in advancing research on fruit edibility. Looking forward, there is substantial potential for further research to expand upon this foundation. Future endeavors could focus on the development of additional databases that encompass a broader range of plant species and conditions. Such expansions would not only enhance the breadth and depth of resources available for fruit quality estimation but also enrich the datasets available for the training and evaluation of deep learning models within this domain. The continued growth in this area of research promises to yield significant advancements, contributing valuable insights and tools to the agricultural and food sciences fields.

4.2 Greenmednet: A computationally inexpensive hyperparameter optimised dual attention based insulin leaves categorization approach

4.2.1 Comprehensive Comparative Results:

In my research, I have conducted a rigorous evaluation of the performance efficiency of my novel neural network architecture by benchmarking it against a suite of established deep neural networks, including AlexNet [12], ResNet152 [14], MobileNetV2 [15], InceptionV3 [16], DenseNet121 [20], InceptionResNetV2 [21], and both variants of NasNet (NasNetLarge [22] and NasNetMobile [22]). The evaluation was based on a series of critical quantitative metrics: Test Accuracy, Precision, Recall, and F1 Score. For an in-depth understanding of these metrics, refer to [26]. The results from these evaluations are comprehensively presented in Table 8.

TABLE VIII: COMPREHENSIVE COMPARATIVE RESULTS

Parameters	**AlexNet [12]**	**ResNet152[14]**	**MobileNetv2[15]**
Test Accuracy (%)	94.29	76.78	94.03
Precision	0.944	0.828	0.94
Recall	0.943	0.767	0.94
F1 Score	0.942	0.753	0.94
Total Parameters	44562890	24106107	7523
Parameters	**Inceptionv3[16]**	**DenseNet121[20]**	**InceptionResNetV2[21]**
Test Accuracy (%)	91.46	90.90	92.75
Precision	0.914	0.913	0.922
Recall	0.914	0.913	0.922
F1 score	0.914	0.913	0.922
Total Parameters	458923	4314289	1114482
Parameters	**NasNetLarge[22]**	**NasNetMobile[22]**	**GreenMedNet**
Test Accuracy (%)	94.88	94.55	**99.47**
Precision	0.948	0.943	**0.995**
Recall	0.948	0.943	**0.995**
F1 Score	0.948	0.943	**0.995**
Total Parameters	1324501	369104	**6521**

4.2.2 Conclusion:

To the best of my knowledge, this study represents a pioneering effort in the detection of diseases in leaves of significant medicinal value, particularly those known for their hypoglycemic properties. A key innovation of this research is the establishment of the Nature's Diabetes Helpers: Insulin Leaves Repository, which includes a collection of both afflicted and healthy leaf samples from species recognized for their glucose-lowering effects. My extensive analysis reveals that the GreenMedNet model adeptly maintains a balance between performance efficiency and the total number of parameters at both the document and word levels. This equilibrium is primarily attributed to the adoption of depth-wise separable convolutions and GlobalAveragePooling2D layers, which substantially minimize the model's parameter footprint. Furthermore, the implementation of a dual attention mechanism—operating across both spatial and channel dimensions—significantly augments the model's efficacy by selectively emphasizing features based on their computed attention scores. The integration of Batch Normalization and Dropout layers, coupled with an L2 regularization strategy, markedly accelerates convergence while mitigating the risk of overfitting.

4.2.3 Prospective research avenues in this domain might include:

a. Accuracy Enhancement: Despite the network's notable performance, there is potential for further enhancement. Future work could explore more advanced learning methodologies, such as deeper architectures, novel neural network frameworks, or ensemble techniques to amalgamate predictions from multiple models.

b. Extension to Additional Crops and Diseases: The current research scope is confined to particular crop species and their associated leaf diseases. Expanding this scope to encompass a broader array of crops and diseases could facilitate the development of more extensive databases and models capable of identifying and classifying a wider range of leaf diseases across various crops.

c. Integration of Real-time Data: Present models predominantly utilize static databases for leaf disease detection. A promising research direction could be the incorporation of real-time data into the detection algorithms, potentially through the use of sensors or cameras that continuously capture and feed live leaf imagery into the detection models for immediate analysis.

d. Mobile Application Development for Leaf Disease Detection: Developing a mobile application based on the leaf disease detection model presents a valuable opportunity. This application would enable end-users, such as farmers, to capture leaf images using mobile devices, upload these images to the application, and swiftly obtain disease detection and classification results.

4.3 Natural vegetable progression evaluation through new developed database (VDBB). Nature's Best vs. Bruised: A Veggie Evaluation

4.3.1 Conclusion: The database represents a significant advancement in the automated assessment of vegetable freshness. By methodically transitioning vegetables from fresh to severely damaged conditions under controlled laboratory settings and capturing these changes through a variety of photographic techniques, I have created a robust dataset that reflects real-world variability. The use of multiple camera angles and inconsistent lighting conditions, paired with a consistent white background, ensures that the data is both challenging and representative of typical operational environments. Furthermore, organizing the images into specific folders based on vegetable category and condition state, all resized to a uniform resolution of 256x256 pixels, facilitates straightforward usability. This meticulously curated database is poised to be an invaluable resource for the development, training, validation, and testing of new algorithms aimed at automating the freshness evaluation of vegetables, potentially revolutionizing quality control processes in the food industry.

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