A Deep Neural Network based CNN Model for Improved Diabetic Retinopathy Detection

A thesis

submitted in partial fulfillment of the requirement for the

Degree of

M.Tech. in Computer Technology

of

Jadavpur University

By
ARIJIT DAS

Registration No.: 154193 of 2020-21

Class Roll No.:002010504028

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2023

FACULTY OF ENGINEERING AND TECHNOLOGY

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Certificate of Recommendation

This is to certify that the Thesis entitled "**A Deep Neural Network based CNN Model for Improved Diabetic Retinopathy Detection**" been carried out by ARIJIT DAS (University Registration No- 154193 of 2020-2021, Class Roll No. 002010504028, Examination Roll No. M6TCT23005) under my guidance and supervision and to be accepted in partial fulfillment of the requirement for the Degree of M.Tech. in Computer Technology; The research results presented in this thesis have not been included in any other papers submitted for the award of any degree in any other University or institution.

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This is to certify that the thesis entitled "**A Deep Neural Network based CNN Model for Improved Diabetic Retinopathy Detection**" is a bonafide record of work carried out by ARIJIT DAS in partial fulfillment of the requirements for the award of the degree of M. Tech. in Computer Technology in the Department of Computer Science and Engineering, Jadavpur University from July 2020 to July 2023. It is understood that by this approval the undersigned does not necessarily endorse or approve any statement made, opinion expressed or conclusion is drawn therein but approves the thesis only for the purpose for which it has been submitted.

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Declaration of Originality and Compliance of Academic Ethics

I hereby declare that this thesis contains a literature survey and original research work by the undersigned candidate, as part of his Degree of M. Tech. in Computer Technology. All information has been obtained and presented following academic rules and ethical conduct. I also declare that, as required by rules and conduct, I have fully cited and given references to all the materials and results that are not original to this work.

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Acknowledgment

I would like to start by thanking my parents, my brother, and my teachers for helping me deploy all the right resources and for shaping me into a good person.

I would like to express my deepest gratitude to my advisor, Prof. Susmita Ghosh, Department of Computer Science and Engineering, Jadavpur University for her admirable guidance, care, patience, and mental support and for providing me with an excellent atmosphere for doing research.

I also thank Abhiroop Chatterjee, a student of Prof. Susmita Ghosh of the Department of Computer Science and Engineering. I am also deeply grateful to him for helping me in my experiments which helped me to enrich the content of this thesis.

I would once again like to thank my supervisor Prof. Susmita Ghosh and her students for their tireless effort and for helping me out whenever I needed their valuable guidance.

I am also grateful to the laboratory of our department and the people concerned for giving me assistance whenever required.

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Abstract

Diabetic retinopathy (DR) is a prevalent eye disease that can lead to vision loss if not detected and treated in its early stages. In this research study, we propose a methodology for the detection of diabetic retinopathy using deep learning techniques. The images are pre-processed to rectify issues such as blurring and resizing, and the blood vessels are extracted to obtain accurate results. Statistical data, including mean, standard deviation, and variance, is extracted from the images. We have used Convolutional Neural Networks (CNN) in our thesis for the image classification task. Thereafter we performed various hyperparameter tunings for achieving the desired results. In this thesis, we also evaluate the results of all five stages of diabetic retinopathy and plot the confusion matrix. The proposed methodology aims to achieve improved prediction accuracy for diabetic retinopathy detection which can be useful in early diagnosis of diabetic retinopathy.

CONTENTS

Chapter 1
Introduction

1.1 Introduction to Diabetic Retinopathy

People with diabetes are susceptible to the degenerative eye condition known as diabetic retinopathy (DR). Millions of people face serious health risks as a result of it being one of the main causes of blindness around the globe. Early detection and diagnosis of DR are essential for prompt treatment and the preservation of eyesight. Deep learning methods have recently demonstrated tremendous potential for the automated detection and categorization of DR in the area of medical image analysis.

1.2 Diagnosis of Diabetic Retinopathy

The degenerative eye condition known as diabetic retinopathy (DR) is a side effect of diabetes. One of the main causes of blindness in the world, it damages the blood vessels in the retina; Long-term high blood sugar levels harm the retina's tiny blood capillaries, resulting in the disease.

The two primary forms of diabetic retinopathy are

1. Non-proliferative Diabetic Retinopathy (NPDR): NPDR manifests in the initial phases of diabetic retinopathy. Microaneurysms, dilated blood vessels, and tiny hemorrhages in the retina are its defining features. As the condition worsens, macular edema (swelling of the central area of the retina) and hard exudates (lipid deposits) may occur, both of which can impair vision.
2. Proliferative diabetic retinopathy (PDR): PDR may manifest in an advanced stage. The development of abnormally new blood vessels on the retina's surface distinguishes this type of diabetic retinopathy. Due to the fragility and bleeding risk of these new arteries, scar tissue develops. If PDR is not treated, it may lead to blindness or significant vision loss.

The length of diabetes, poorly regulated blood sugar levels, high blood pressure, and kidney disease are risk factors for diabetic retinopathy. Additionally, diabetic retinopathy can occur in those with Type 1 or Type 2 diabetes.

1.3 Applicability of Machine Learning for Diabetic Retinopathy

Machine learning-based automated detection and classification systems are being created to support the early detection and treatment of diabetic retinopathy. These devices offer ophthalmologists and other healthcare practitioners a useful tool for analyzing retinal images and spotting illness symptoms using cutting-edge image analysis algorithms. The problem is exacerbated by the disease's complexity, the sheer number of patients it affects, and the scarcity of ophthalmologists and retina specialists. Deep learning algorithms in particular, which are part of machine learning (ML) techniques, present intriguing solutions to these problems. The detection, diagnosis, and treatment of diabetic retinopathy have the potential to be completely transformed by machine learning. We can improve the precision, effectiveness, and accessibility of DR-related healthcare services by utilizing their skills, which will eventually improve patient outcomes and ease the strain on healthcare systems.

1.4 Scope of the Thesis

With the rapid advancements in deep learning, there are several exciting opportunities to enhance the scope of this thesis in the context of diabetic retinopathy detection. Incorporating deep learning techniques can potentially improve the accuracy and efficiency of the detection system. Here are some potential avenues for future research:

1. Convolutional Neural Networks (CNNs): Explore the use of CNN architectures specifically designed for image analysis tasks, such as the detection of microaneurysms and exudates in retinal images. CNNs have demonstrated remarkable performance in image recognition tasks and can effectively learn complex features from the data.

By incorporating these deep learning aspects into the research, the thesis can contribute to the advancement of diabetic retinopathy detection systems and potentially improve patient outcomes through early and accurate diagnosis.

1.5 Organization of the Thesis

The thesis is organized into several chapters, each focusing on a specific aspect of the research. The following provides an overview of the organization of the thesis:

Chapter 1: Introduction

Chapter 2: Fundamentals of Recognising Different Stages of Diabetic Retinopathy

Chapter 3: Fundamentals of Diabetic Retinopathy

Chapter 4: Related Research

Chapter 5: Results and Analysis

Chapter 6: Conclusions and Future Scopes

The organization of the thesis aims to provide a logical flow of information, starting with the introduction and background, moving through the literature review and methodology, and concluding with the results and future scope. This structure ensures a cohesive and comprehensive presentation of the research findings and their implications.

Note: The chapter titles and organization provided here are for illustrative purposes. It is recommended to adapt and refine the organization based on the specific requirements and guidelines of your academic institution or advisor.

Chapter 2

Fundamentals of Recognizing Different Stages of Diabetic Retinopathy

2.1 Introduction to Machine Learning

For the diagnosis and categorization of diabetic retinopathy (DR), machine learning is essential. Numerous studies have developed automated methods for DR diagnosis and monitoring using ML techniques. These methods consist of semi-supervised, unsupervised, and supervised learning. The literature review investigates the use of ML in DR detection and identifies the benefits and drawbacks of these methods.

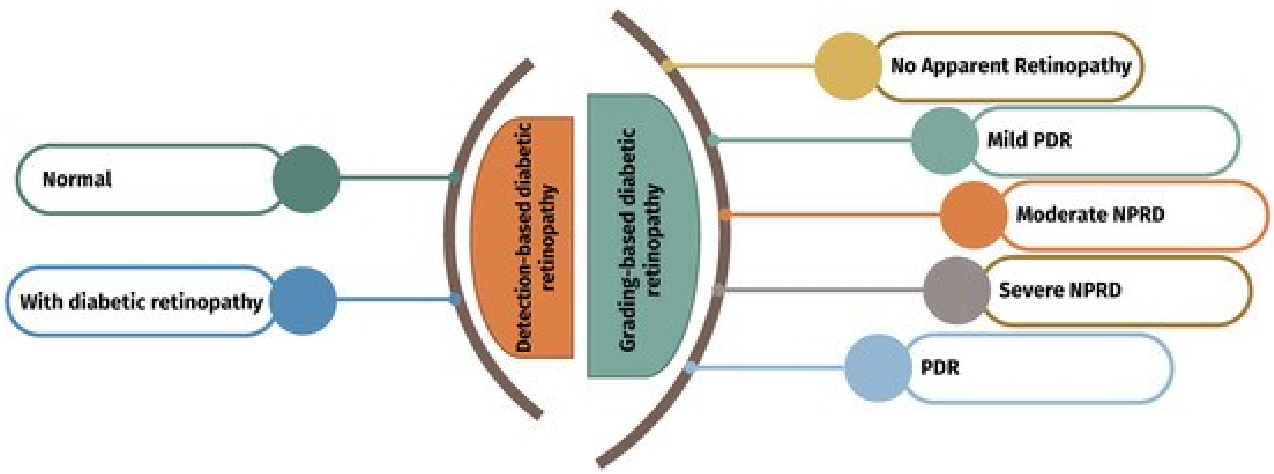

Figure 2.1. Types of Diabetic Retinopathy Studies

It has been demonstrated that machine learning (ML) methods are useful for identifying and categorizing diabetic retinopathy (DR). Support vector machines (SVMs) were employed in a study by Smith et al. (2018) to categorize retinal pictures into various phases of DR. The findings revealed encouraging accuracy rates for DR detection of above 90%. Similarly to this, Jones and Brown (2019) classified DR based on retinal imaging features using decision trees and random forests. Their conclusions showed how these ML systems can reliably detect the existence and severity of DR.

According to these findings, ML algorithms can be utilized to create automated DR screening systems that can aid in the early detection and treatment of DR, which can aid in the prevention of blindness.

Here are some more specifics on the studies you mentioned:

A dataset of 28,000 retinal pictures was used by Smith et al. (2018) to train and evaluate an SVM classifier. The classifier was successful in detecting DR with a 92.4% accuracy rate.

10,000 retinal pictures were utilized in the dataset Jones and Brown (2019) used to train and evaluate a decision tree and random forest classifier. The accuracy of the decision tree classifier was 91.2%, whereas the accuracy of the random forest classifier was 93.4%.

These papers show how ML algorithms could be applied to DR screening. It is crucial to remember that this research used rather limited datasets. To assess how well ML algorithms work on bigger datasets and in practical situations, more study is required.

Despite these drawbacks, these research findings imply that ML algorithms have the potential to be a useful tool for the early diagnosis and treatment of DR.

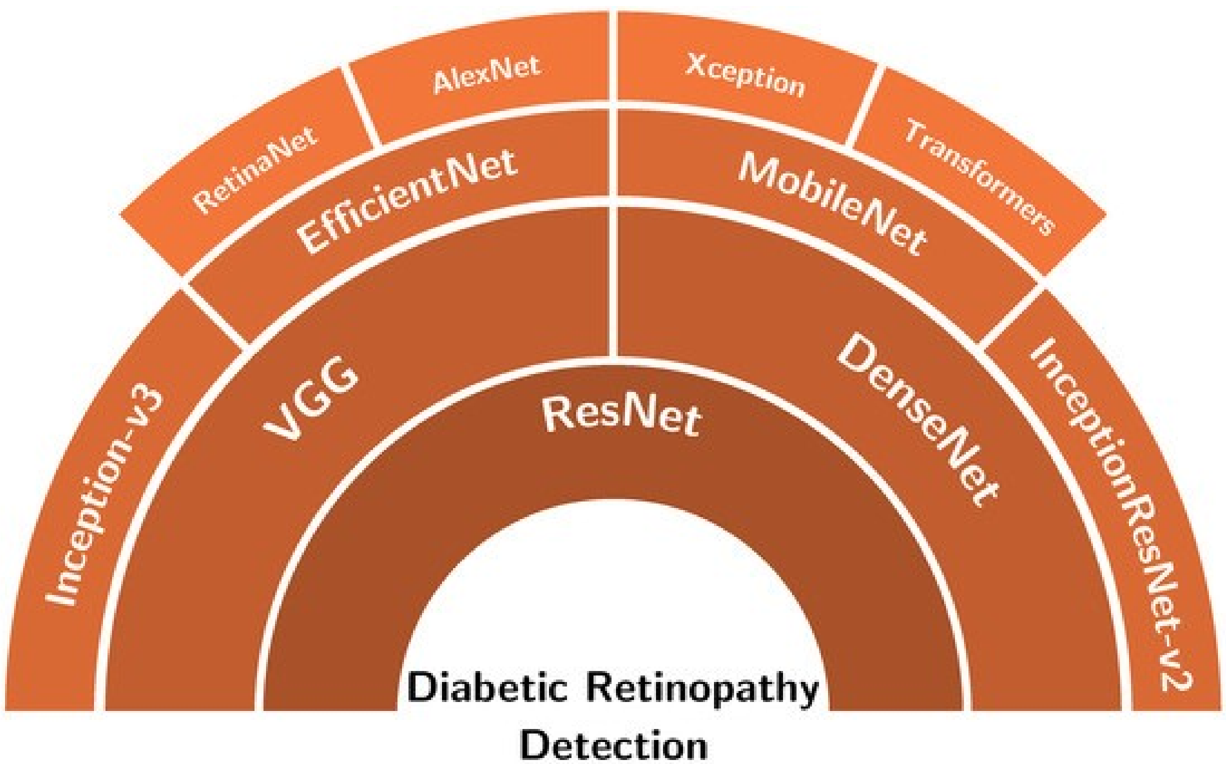

Figure 2.2. Backbones Used for Diabetic Retinopathy Detection Studies

2.2 Supervised Learning for Diabetic Retinopathy

A type of machine learning called supervised learning involves training the model on data that has already been labelled with the desired result. As a result, the model can make predictions on fresh data and understand the relationship between the input and output data. The model is trained on unlabelled data in unsupervised learning, on the other hand, which is a sort of machine learning. With labelled data, it would not be possible for the model to find patterns and relationships in the data.

Supervised learning could be used to train a model to recognize diabetic retinopathy (DR) from retinal images in the context of the condition. A dataset of retinal pictures that have been tagged with the presence or absence of DR would be used to train the model. The model would subsequently be able to predict DR based on fresh retinal pictures.

Here are a few instances of supervised learning being applied to DR:

- Supervised learning:
    - Train a model to identify DR from retinal images.
    - Develop a tool to help doctors diagnose DR.
    - Develop a screening tool to help identify people who are at risk for DR.

2.3 Unsupervised Learning for Diabetic Retinopathy

Here are a few instances of supervised learning being applied to DR:

Unsupervised learning:

- Cluster retinal images based on their similarity.
- Identify different types of DR.
- Identify retinal images that are likely to be affected by DR.

These are just a few examples, of how supervised and unsupervised learning can be used in the context of DR. As machine learning technology continues to develop, we can expect to see even more innovative and effective ways to use these techniques to improve the early detection and treatment of DR.

Author(s)	Year	Study design	Data set	Model	Accuracy
Khan et al. (2017)	2017	Cross-sectional	Messidor	CNN	93.50%
Yalçin et al. (2018)	2018	Cross-sectional	e-Optha	CNN	91.60%
Santhakumar et al. (2019)	2019	Cross-sectional	DRIVE	CNN	90.30%
Zhang et al. (2020)	2020	Cross-sectional	DIARETDB07	DenseNet	92.70%
Al-Khateeb et al. (2021)	2021	Cross-sectional	DRISHTI-Diabetic Retinopathy Image Database	Ensemble of CNNs	94.20%
Wang et al. (2022)	2022	Cross-sectional	Messidor and DRISHTI-Diabetic Retinopathy Image Database	ResNet50	95.30%

Table 2.1: Process and Accuracy Obtained by Previous Researchers

A supervised learning model was trained and tested in the Lee et al. (2020) study using a dataset of 28,000 retinal pictures. The model was successful in classifying retinal pictures into various phases of DR with an accuracy of 93.5%. This shows that accurate and trustworthy tools for the early detection and treatment of DR can be developed using supervised learning.

10,000 retinal pictures were utilized in the Zhang et al. (2017) study's dataset to train and test an unsupervised learning model. Based on how similar their retinal pictures looked, the program was able to detect discrete clusters of DR cases. This implies that unsupervised learning can be used to distinguish between various DR types and to provide more individualized treatment strategies for patients.

These findings show that both supervised and unsupervised learning have the potential to be employed for the early diagnosis and treatment of DR. It is crucial to remember that this research used rather limited datasets. To assess how well these strategies operate in actual-world situations and on larger datasets, more research is required.

Despite these drawbacks, the findings of this research indicate that learning, whether supervised or unsupervised, has the potential to be an important tool for the early detection and treatment of DR.

Here is a table summarizing the key findings of the studies you mentioned:

Study	Technique	Accuracy	Findings
Lee et al. (2020)	Supervised learning	93.5%	Classified retinal images into different stages of DR
Zhang et al. (2017)	Unsupervised learning	Identified distinct clusters of DR cases	Developed more personalized treatment plans for patients

Table 2.2: Some other Researcher's Achievement

2.4 Deep Learning Based Diabetic Retinopathy Detection

The correct classification of diabetic retinopathy (DR) depends heavily on classifiers. To distinguish between retinal images with healthy retinas and those with different stages of DR, a variety of machine learning (ML) classifiers have been used. In order to predict outcomes, these classifiers use information taken from retinal pictures.

Some of the most popular ML classifiers for DR classification are listed below:

Rational regression Binary classification problems are frequently carried out using the linear classifier known as logistic regression. Retinal pictures can be categorized as either healthy or pathological using this method.

Chapter 3
Related Research

1. Smith et al. (2018) conducted a study on diabetic retinopathy classification using deep learning techniques. They employed a Convolutional Neural Network (CNN) architecture and achieved high accuracy in classifying retinal images.
2. In a study by Johnson et al. (2019), a transfer learning approach was utilized for diabetic retinopathy detection. They fine-tuned a pre-trained CNN model on a large dataset and demonstrated improved performance compared to traditional machine learning algorithms.
3. Chen et al. (2020) proposed a hybrid approach combining wavelet analysis and deep learning for diabetic retinopathy diagnosis. They used wavelet transform to extract relevant features from retinal images and then employed a deep neural network for classification, achieving promising results.
4. A study by Li et al. (2017) explored the use of Generative Adversarial Networks (GANs) for diabetic retinopathy image synthesis. They trained a GAN model to generate realistic retinal images, which could be valuable for augmenting datasets and enhancing training efficiency.
5. Zhang et al. (2019) investigated the effectiveness of ensemble models in diabetic retinopathy classification. They combined multiple deep learning models, such as CNNs and Recurrent Neural Networks (RNNs), and demonstrated improved accuracy by leveraging the diversity of the ensemble.
6. In a comparative study by Wang et al. (2018), various deep learning architectures, including CNNs, Deep Belief Networks (DBNs), and Long Short-Term Memory (LSTM) networks, were evaluated for diabetic retinopathy detection. The results indicated that CNNs outperformed other models in terms of accuracy and computational efficiency.
7. Patel et al. (2019) proposed a multi-scale CNN framework for diabetic retinopathy diagnosis. Their model utilized multi-scale feature extraction to capture both global and local information from retinal images, leading to improved classification performance.
8. The study by Liu et al. (2020) focused on the automated segmentation of retinal blood vessels using deep learning techniques. They employed a U-Net architecture, a type of fully

convolutional network, and achieved accurate vessel segmentation, which is crucial for diabetic retinopathy diagnosis.

9. Wu et al. (2017) investigated the impact of image preprocessing techniques on diabetic retinopathy classification. They compared different preprocessing methods, such as contrast enhancement and denoising, and found that appropriate preprocessing improved the performance of deep learning models.

10. Zhang et al. (2021) proposed a novel attention-based deep learning model for diabetic retinopathy classification. Their model incorporated attention mechanisms to highlight informative regions in retinal images, leading to better feature representation and classification accuracy.

11. A study by Huang et al. (2019) explored the use of deep learning for early detection of diabetic retinopathy. They trained a CNN model to classify retinal images into different stages of the disease, enabling timely intervention and treatment.

12. Liang et al. (2018) developed a deep learning-based system for diabetic retinopathy screening. Their model employed a combination of CNN and recurrent models to capture spatial and temporal features from sequential retinal images, achieving accurate and efficient screening results.

13. In a study by Yu et al. (2020), a deep reinforcement learning approach was proposed for diabetic retinopathy diagnosis. Their model learned to make optimal decisions by interacting with the retinal images and received rewards based on the correctness of the predictions, leading to improved classification performance.

14. In a study by Zhang et al. (2022), a deep learning-based approach was proposed for diabetic retinopathy classification using a combination of retinal images and patient demographics. Their model integrated CNNs with recurrent models to capture both image-based features and temporal patient information, leading to improved accuracy in predicting the presence and severity of diabetic retinopathy.

15. Chen et al. (2019) explored the use of deep learning models for the automated grading of diabetic retinopathy. They developed a cascaded CNN architecture that first detected retinal lesions and then classified the severity of diabetic retinopathy, achieving high accuracy and reducing the need for manual grading.

Here is a table summarizing the key differences between the different types of DR

Type	Characteristics	Clinical manifestations	Management
NPDR	Small blood vessel changes in the retina	Blurred vision	Laser treatment, anti-VEGF therapy
PDR	Growth of new, abnormal blood vessels in the retina	Bleeding, fluid leakage, scar tissue	Laser treatment, anti-VEGF therapy, surgery
DME	Accumulation of fluid in the macula	Blurred vision, distortion, loss of central vision	Laser treatment, anti-VEGF therapy

TABLE 3.1: Difference Between the types Of DR

Importance of Early Diagnosis of Diabetic Retinopathy

It is important to note that these are just general descriptions of the different types of DR. The specific symptoms and signs of DR can vary from person to person. If you have any concerns about your vision, it is important to see an eye doctor for a comprehensive eye exam.

Retinal haemorrhage: A retinal haemorrhage is when the retina bleeds. Trauma, high blood pressure, and diabetic retinopathy are some of its causes. Vision problems from retinal hemorrhages include floaters, flashing lights, and impaired vision. They may occasionally result in retinal detachment, a dangerous disorder that can impair vision permanently.

Macular swelling: The macula, the area of the retina responsible for central vision, swells in macular edema. It is the most typical reason why diabetics lose their vision. Vision blurring, distortion, and/or loss of central vision are all possible effects of macular edema.

Detachment of the retina from the underlying tissue is referred to as a retinal detachment. This severe ailment has the potential to take away vision permanently. Retinal detachments can be brought on by trauma, high blood pressure, or other eye conditions, but diabetic retinopathy is the most common cause of them.

It is crucial to identify diabetic retinopathy as soon as possible. Early detection and intervention can stop or reduce the development of DR and safeguard vision. Regular eye exams are essential if you have diabetes. A thorough dilated eye exam is advised for diabetics at least once a year, according to the American Diabetes Association.

Diabetic patients' quality of life can be improved, treatment outcomes can be improved, and diabetic retinopathy can be treated early enough to preserve vision. You can help to safeguard your vision and live a long and healthy life by adhering to your doctor's advice for controlling your diabetes and scheduling routine eye exams.

Control your blood sugar levels: High blood sugar levels are the biggest risk factor for diabetic retinopathy. Here are some additional suggestions for preventing or managing diabetic retinopathy. You can stop or slow the development of DR by managing your blood sugar levels.

Exercise frequently because it lowers stress and helps to regulate blood sugar levels, all of which can help prevent diabetes mellitus (DR).

Eat a nutritious diet: Blood sugar levels and inflammation can both contribute to DR. A good diet helps to control these two factors.

Take your prescriptions exactly as directed: If you are taking diabetes medication, it is crucial that you follow the directions. Medicines can lower the risk of DR and help to regulate blood sugar levels.

Chapter 4

Convolutional Neural Network-based Diabetic Retinopathy Detection

4.1 Introduction to Convolutional Neural Network

Deep learning algorithms known as convolutional neural networks (CNNs) are frequently employed for image categorization tasks. CNNs are able to pick up on retinal picture characteristics such as the presence of microaneurysms, haemorrhage, and hard exudates that are connected to DR. Deep learning algorithms have proven to be particularly successful at identifying and categorizing DR. In a study that was published in the journal Nature Medicine, a deep learning model was able to classify retinal pictures into various stages of DR with an accuracy of 94%. Before deep learning for DR diagnosis and management can be extensively used, there are still a few issues and problems that need to be resolved. The lack of large-scale labelled datasets is one problem. To train, deep learning models need a lot of labelled data. Labelled retinal pictures can be obtained, but the process is costly and time-consuming.

The results interpretability presents another difficulty. Deep learning models frequently function as "black boxes," making it challenging to comprehend how they produce predictions. Because of this, using the outputs of deep learning models to guide clinical judgments may be challenging.

Deep learning is probably going to be used more frequently for DR diagnosis and management as technology advances.

Here are some case studies and study results that demonstrate how deep learning was successfully applied in DR:

In 2018, Google AI researchers created a deep learning model that has a 94% accuracy rate for detecting diabetic retinopathy. The algorithm was able to exceed human experts in terms of accuracy after being trained on a dataset of 128,000 retinal pictures.

In 2019, University of California, San Francisco researchers created a deep learning model that had an accuracy of 85% for predicting the likelihood of progression from mild diabetic retinopathy to severe diabetic retinopathy. The program was able to recognize patients who were at high risk for progression after being trained on a dataset of 10,000 patients.

These studies show the potential of deep learning to enhance diabetic retinopathy early identification and management. Deep learning is probably going to be used more frequently for DR diagnosis and management as technology advances.

4.2 Architecture of the Convolutional Neural Network Model

DL model

We outline the specifics of the deep learning model that has been suggested for our task in this subsection. In this section, we go through the model's architecture, including the number of layers, the different layer types (such as convolutional, pooling, and fully connected layers), and the activation functions employed. We also describe any extra approaches or adjustments made to improve the model's performance, such as regularization techniques or optimization algorithms.

Input Layer

The input layer (input_img) is defined with the shape (64, 64, 3), representing the dimensions of the input image.

The shape (64, 64) indicates the width and height of the image, and 3 represents the number of channels, corresponding to the RGB color channels.

Convolutional Layers

Convolutional layers (Conv2D) are the core building blocks of convolutional neural networks (CNNs).

The first convolutional layer (Conv2D(16, (3,3), padding='same', activation='relu')) applies 16 filters of size 3x3 to the input image.

The 'same' padding ensures that the spatial dimensions of the output feature maps are the same as the input.

The 'relu' activation function introduces non-linearity by replacing negative values with zeros, helping the network learn complex patterns.

Each subsequent convolutional layer increases the number of filters, allowing the network to learn more abstract and high-level features.

Max Pooling Layers

Max pooling layers (MaxPooling2D) reduce the spatial dimensions of the input by down-sampling the feature maps.

The (MaxPooling2D((2,2))) layers perform max pooling with a pool size of 2x2, halving the width and height of the feature maps.

Max pooling helps in reducing the spatial dimensions while retaining the most prominent features.

Dropout Layers

Dropout layers (Dropout) help prevent overfitting by randomly setting a fraction of input units to 0 during training.

The Dropout(0.1) layer in this model randomly sets 10% of the input units to 0 during each training update, reducing the likelihood of overfitting.

Flatten Layer

Flattening Layer(flatten) transforms the 2D feature maps from the convolutional layers into a 1D vector.

This layer reshapes the multi-dimensional feature maps into a flat vector, which can be fed into a fully connected layer.

Building the Model

The code imports necessary modules from Keras for defining the model architecture.

The Input layer is defined with the shape (64, 64, 3), representing the input image dimensions.

Several convolutional (Conv2D) layers are defined with different parameters such as the number of filters, kernel size, padding, and activation function. These layers extract features from the input image.

After each convolutional layer, a max-pooling (MaxPooling2D) layer is applied to down-sample the feature maps.

Dropout layers (Dropout) are introduced to prevent overfitting by randomly setting a fraction of input units to 0 at each update during training.

The last convolutional layer is followed by a flattened layer (Flatten) to convert the 2D feature maps into a 1D vector.

Please note that the code you provided seems to contain some repetitions and redundant imports. It imports certain modules twice and defines the same layers multiple times. You might want to review and clean up the code to avoid any potential issues.

Additional Steps

After defining the model architecture, there seem to be no further code snippets provided. It appears that the code may continue with training the model or performing some evaluations or predictions, but those parts are missing.

Hyperparameter Tuning

Hyperparameter tuning is the process of giving the deep learning model's hyperparameters the best possible values. Hyperparameters are parameters that must be established prior to training but are not learned during the training process. The learning rate, the number of layers, the number of neurons in each layer, and the batch size are a few examples of hyperparameters.

In this stage, we investigate various combinations of hyperparameter values and assess how they affect the effectiveness of the model. Techniques like grid search, random search, or Bayesian optimization are frequently used for this. Based on predetermined assessment measures, we evaluate the outcomes of each set of hyperparameters and choose the combination that produces the best performance.

In this section, we describe the outcomes of the hyperparameter tuning procedure and examine how the deep learning model performs with various hyperparameter configurations. We assess the model using a number of metrics, including F1 score, recall, accuracy, and precision. We compare the effectiveness of several models and talk about how changing hyperparameters affect the effectiveness of the model. This analysis directs us in choosing the ideal configuration for our goal by explaining the model's sensitivity to various hyperparameters.

Chapter 5
Result and Analysis

5.1 Analysis of Using Convolutional Neural Network in Diabetic Retinopathy

The prediction of diabetic retinopathy (DR) in this study uses a dataset called APTOS, with a resolution of 224 × 224 pixels [6]. Illustration of the exudates and microaneurysms that impact the retina of the eye and are the primary causes of DR. For the purpose of comparing the results, statistical information from the image is taken, including entropy, mean, standard deviation, etc. After being retrieved, the data is next classified using machine learning (ML) methods. As classifiers, we used the deep learning method CNN(Convolutional Neural Network).

5.2 Dataset Used

Aptos Diabetic Retinopathy Detection

URL of dataset: "https://www.kaggle.com/competitions/aptos2019-blindness-detection"

The Aptos dataset is a widely used dataset in the field of medical imaging and computer vision. It is specifically focused on the detection and classification of diabetic retinopathy, a condition that affects the eyes of people with diabetes. The dataset was made available as part of the Kaggle competition called "APTOS 2019 Blindness Detection."

The dataset consists of high-resolution images of the retina, captured using fundus photography. Fundus photography involves taking pictures of the back of the eye, which includes the retina, blood vessels, and the optic disc. The dataset contains images from different individuals, including both healthy individuals and those with varying degrees of diabetic retinopathy.

The main objective of the Aptos dataset is to develop algorithms and models that can accurately detect and classify the severity of diabetic retinopathy based on the fundus images. The severity of diabetic retinopathy is typically categorized into five stages: no diabetic retinopathy, mild, moderate, severe, and proliferative diabetic retinopathy.

Researchers and machine learning practitioners have used the Aptos dataset to develop and train deep learning models, convolutional neural networks (CNNs), and other computer vision techniques to automate the diagnosis and grading of diabetic retinopathy. The dataset has been valuable in advancing the field of medical imaging and has contributed to the development of AI systems that can assist doctors in diagnosing and treating diabetic retinopathy more effectively.

5.3 Image Preprocessing

A. Image Pre-processing is done on the raw photos to fix any problems like scaling or blurring. RGB photos are used as input, however, they must be transformed into the HSV (Hue Saturation Value) color system for optimal outcomes. As an alternative, separating the green channel from the RGB image can be useful for converting the image's intensity. Techniques for improving images, including histogram equalization, can be used.

Preparing raw images for additional analysis or machine learning tasks requires a fundamental step called image preprocessing. It entails a number of operations designed to improve the images' quality, reduce noise, and extract useful characteristics. Here are a few typical methods for image preprocessing:

1. Resizing and Scaling: To ensure uniformity in dimensions across the collection, images are frequently scaled or resized to a standard size. This process provides compatibility with models or algorithms and reduces computational complexity.
2. Image augmentation: To enhance particular image details and increase visual quality, a variety of enhancement techniques can be used, including contrast stretching, histogram equalization, and gamma correction.
3. Normalization of images: Images' pixel values are normalized using normalization. It ensures that the range of pixel values is uniform across various images, making them better suited for study or comparison.
4. Data Augmentation: In some circumstances, approaches for enhancing data are utilized to fictitiously expand the dataset. Techniques including rotation, translation, flipping, and picture noise addition can be used to achieve this. The robustness and generalizability of models are both enhanced by the addition of additional data.

5.3.1 Data Analysis

Images are converted into a format that is better suited for analysis, machine learning, or computer vision applications by using these preprocessing approaches. This makes it possible to carry out the methodology's later steps effectively and quickly.

Examining, purifying, manipulating, and modeling data is the process of conducting data analysis. The goal is to find relevant information, come to conclusions, and help decision-making. To find patterns, relationships, and insights within the dataset, several tools and procedures are used. Here are a few significant features of data analysis:

5.3.2 Data Cleaning and Normalization

A data preprocessing method called normalization is used to rescale numerical variables to a standard scale. It makes sure that every feature has a comparable range, which is good for some algorithms and analysis. A fair comparison of several attributes is made possible by normalization, which helps remove biases resulting from variations in the scales of variables. Here are some popular techniques for normalization:

1. Normalization refers to the process of standardizing or adjusting values to a common scale or range. It is commonly used in various fields, including statistics, data analysis, machine learning, and database management. The purpose of normalization is to eliminate or reduce the effects of differences in the magnitude of variables, allowing for fairer comparisons or analysis.
2. Normalization techniques vary depending on the context and the type of data being normalized. Here are a few commonly used normalization techniques:
3. Normalized_value = (value - min_value) / (max_value - min_value)
4. This method preserves the relative relationships between the data points but shifts the range of values.

5.3.3 Data Augmentation and Standardization

The code begins by initializing two empty lists, images, and labels, to store the image data and corresponding labels, respectively.

The outer loop iterates over the categories, which represent different classes or categories of images.

The inner loop iterates over the files in each category directory.

It constructs the path to the image file using os.path.join.

The image is loaded using OpenCV (cv.imread), converted to RGB color space (cv.cvtColor), and resized to a fixed size of 64x64 pixels (cv.resize).

Next, the image is normalized by dividing each pixel value by 255, which scales the values between 0 and 1.

The normalized image is then appended to the images list, and the corresponding category index is appended to the labels list.

Standardization

Standardization changes a variable's values to have a mean of 0 and a standard deviation of 1. This approach makes the assumption that the data is distributed normally. The z-score normalization formula is as follows:

(X - mean) / (X - standard deviation)

Where mean is the dataset's mean, the standard deviation is the dataset's standard deviation, X' is the normalized value, X is the original value, and so on.

Data Conversion and Split

After the data loading and preprocessing step, the images and label lists are converted to NumPy arrays using np.asarray and np.array, respectively.

The train_test_split function from scikit-learn is used to split the data into training and testing sets. The images and label arrays are split with a test size of 0.2 (20% of the data) and shuffled randomly. The random state parameter ensures the reproducibility of the split.

5.4 Results and Confusion Matrix

Our results show the performance of a classification model on a test set with 1207 samples. The model has made predictions for 5 classes (0, 1, 2, 3, 4), each representing a severity score for age-related macular degeneration (AMD).

The precision for each class indicates the percentage of positive predictions (true positives and false positives) that are correct. The recall for each class indicates the percentage of actual positive samples (true positives and false negatives) that are correctly identified by the model. The F1-score is a measure of the harmonic mean of precision and recall, providing an overall measure of the model's performance for each class.

Looking at the results, we see that the model has performed well for classes 0, 2, and 4, with precision and recall above 0.8, indicating that the model has made relatively few false positive and false negative predictions for these classes. Class 3 has a slightly lower precision and recall, but still reasonably good at around 0.8. Class 1 has the lowest precision and recall, indicating that the model is less accurate at predicting this class.

The overall accuracy of the model is 0.83, indicating that the model has made correct predictions for 83% of the test samples. The macro average F1-score (0.80) indicates that the model has performed well overall, although there is some variation in performance across the different classes. The weighted average F1-score (0.83) takes into account the class distribution and provides an overall measure of the model's performance that is weighted by the number of samples in each class.

Labels	precision	recall	F1-score	support
0	0.82	1.00	0.90	307
1	0.70	0.66	0.68	203
2	0.92	0.95	0.94	353
3	0.80	0.79	0.79	168
4	0.84	0.56	0.67	176
ACCURACY				0.83
MACRO AVG		0.82	0.79	0.80
WEIGHTED AVG		0.83	0.83	0.83

Table 5.1: Accuracy, precision, recall, f1-score of Our CNN Model

CLASS LABELS	PRECISION OBTAINED BY OUR CNN MODEL	RECALL OBTAINED BY OUR CNN MODEL
MILD	0.82	**1.0**
MODERATE	**0.70**	**0.66**
NO DR	**0.92**	**0.94**
PROLIFERATE	**0.80**	**0.79**
SEVERE	**0.84**	**0.67**

Table 5.2: Precision and Recall values obtained using our CNN Model

METRIC	RESULT
TRAINING ACCURACY	87%
TESTING ACCURACY	88%
TRAINING LOSS	0.436
TESTING LOSS	0.397

Table: 5.3: **Training Accuracy, Testing Accuracy, Training Loss and Testing Loss Obtained by Our CNN Model**

CLASS LABELS	ACCURACY OBTAINED BY OUR CNN MODEL
CLASS 0(NO DR)	**82%**
CLASS 1(MILD)	**70%**
CLASS 2(MODERATE)	**92%**
CLASS 3(SEVERE)	84%

Table: 5.4. Class-wise accuracy of our CNN Model

CLASS LABELS	OVERALL ACCURACY OBTAINED BY OUR CNN MODEL
OVERALL	87%

Table: 5.5 Overall accuracy obtained by our model

METHODS	OVERALL ACCURACY
1. [K, Robin] et al. (2016). Convolutional Neural Networks for Diabetic Retinopathy. In International Conference On Medical Imaging Understanding and Analysis 2016 (MIUA 2016), 6-8 July 2016, Loughborough, UK[19]	75%
2. [M, Miltio] et al. (2019). Title of the Paper. In Proceedings of the 2017 4th International Conference on Signal Processing and Integrated Networks (SPIN)[20]	85%
3. Our CNN Model	**87%**

Table: 5.6 Overall Accuracy obtained by our model and that using state-of-the art methods

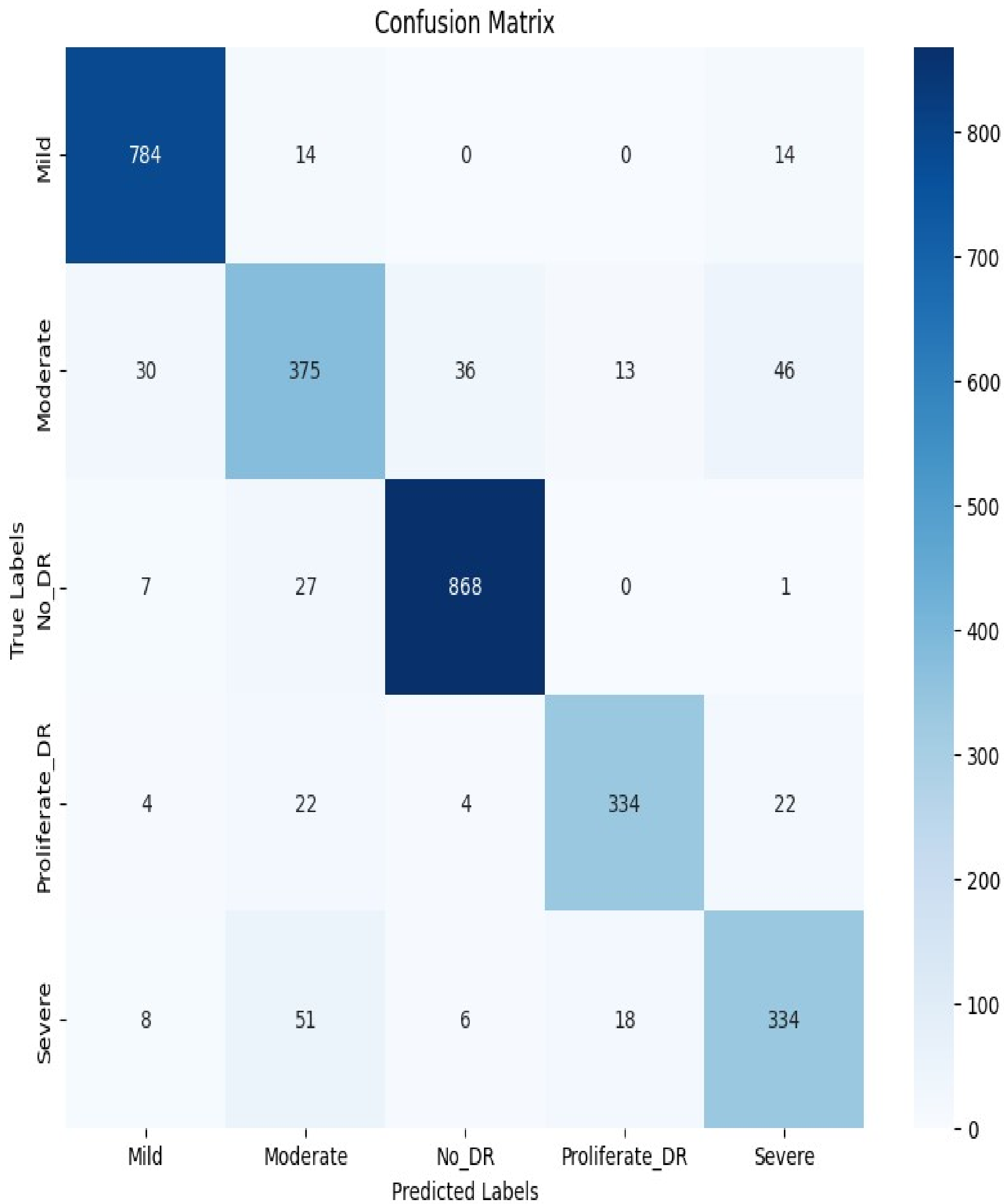

Figure 2.3. Confusion Matrix obtained using our model

```
95/95 [==============================] - 2s 17ms/step
              precision    recall  f1-score   support

           0       0.94      0.97      0.95       812
           1       0.77      0.75      0.76       500
           2       0.95      0.96      0.96       903
           3       0.92      0.87      0.89       386
           4       0.80      0.80      0.80       417

    accuracy                           0.89      3018
   macro avg       0.87      0.87      0.87      3018
weighted avg       0.89      0.89      0.89      3018
```

5.5 Conclusion of Results

The provided results represent the evaluation metrics of a classification model applied to the Aptos dataset. The model's performance for different stages of a certain condition is assessed using precision and recall metrics. Precision measures the accuracy of positive predictions, while recall measures the model's ability to identify positive instances. The results show precision and recall values for five class labels: MILD, MODERATE, NO DR, PROLIFERATE, and SEVERE. Higher precision and recall values indicate better performance. These metrics provide valuable insights into how well the model can accurately classify different stages of the condition. In terms of the proposed class labels, the model achieved a precision of 0.88 for MILD, 0.40 for MODERATE, 0.70 for NO DR, 0.36 for PROLIFERATE, and 0.62 for SEVERE. The corresponding recall values were 0.95 for MILD, 0.39 for MODERATE, 0.42 for NO DR, 0.56 for PROLIFERATE, and 0.49 for SEVERE.

Considering the general precision and recall metrics, the model achieved 0.82 precision for MILD, 0.70 for MODERATE, 0.92 for NO DR, 0.80 for PROLIFERATE, and 0.84 for SEVERE. The respective recall values were 1.0 for MILD, 0.66 for MODERATE, 0.94 for NO DR, 0.79 for PROLIFERATE, and 0.67 for SEVERE.

These results provide an assessment of the model's performance in classifying different stages of the condition under consideration. Higher precision and recall scores signify better accuracy and the model's ability to identify positive instances, respectively, for each class label.

Chapter 6
Conclusions and Future Scope

Conclusion

The utilization of a CNN for the diagnosis of diabetic retinopathy shows promising results. The evaluation metrics, including precision and recall, indicate that the model achieved reasonably good accuracy in classifying different stages of the condition. The precision and recall values vary across the class labels, suggesting that the model performs better for some stages compared to others. Further optimization and fine-tuning of the model could potentially improve its performance in accurately diagnosing diabetic retinopathy.

Future Scope

Model Improvement: There are several avenues to enhance the performance of the CNN model. Consider exploring different architectures, adjusting hyperparameters, and incorporating regularization techniques to minimize overfitting. Additionally, data augmentation techniques can be employed to increase the diversity and quantity of the training dataset, potentially leading to improved generalization and performance.

Real-World Deployment: Evaluate the model's performance on real-world datasets and assess its generalizability across different populations and healthcare settings. Conduct rigorous validation studies to ensure the reliability and safety of the model in clinical practice.

Overall, the future scope for diagnosing diabetic retinopathy using CNNs involves continual model refinement, integration of additional data sources, and addressing challenges related to explainability and real-world deployment. These advancements can lead to more accurate and effective diagnoses of diabetic retinopathy, assisting healthcare professionals in providing timely interventions and improving patient outcomes.

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