Abstract

Lung cancer continues to be one of the most prevalent and fatal cancers worldwide, accounting for a significant proportion of cancer [1]. Despite advances in treatment, the prognosis remains poor, largely due to late-stage diagnosis. Many studies highlight the urgent need to improve early detection methods to enhance patient survival rates. The variability in lung cancer histopathology and the complexity of tumor morphology further complicate diagnosis. This global health challenge necessitates innovative approaches that can effectively support clinicians in detecting and characterizing lung cancer at earlier, more treatable stages. Imaging modalities such as Computed Tomography (CT) scans have become the gold standard for detecting lung nodules, offering high-resolution, three-dimensional visualization of lung tissue [2]. Techniques like convolutional neural networks (CNNs), recurrent networks, and transformer models have demonstrated superior performance in segmenting complex structures and classifying cancerous tissues compared to traditional methods. These models automatically learn hierarchical features directly from data, circumventing the need for manual feature engineering.

Many recent studies have successfully applied deep learning to CT and histopathology images, demonstrating improved accuracy, reproducibility, and speed. The ability of deep learning to handle large-scale datasets and capture subtle image patterns presents an opportunity to enhance lung cancer diagnosis significantly. The literature shows that researchers are extensively experimenting to solve this problem. However, given their real-life societal impacts, their performances are still inadequate. Furthermore, the increasing technological advancements in this domain necessitate more such work to find a solution. With significant advancements in ML and DL over the last decade, several methods have been proposed that

improve the accuracy of determining whether a lung cancer nodule is benign or malignant. In ML algorithms, need to extract features from the inputs in a handcrafted manner, and pass those features to the classifier for classification. On the other hand, DL based models like different CNN models extract the features from the input automatically, i.e., without any manual intervention [3] [4] [5].

One critical application of DL in lung cancer research is medical imaging analysis. The utilization of CNNs in automated feature extraction and classification of lung nodules on CT scans [6] is further explored. These models can assist radiologists in rapidly identifying suspicious lesions, distinguishing between malignant and benign nodules, and providing valuable insights into tumor characteristics such as size, shape, and texture.

The present thesis work is primarily focused on the development of deep learning-based systems for automated detection, classification, and segmentation of lung cancer using medical imaging data. With the increasing availability of annotated radiological scans such as CT, CNNs and attention-based architectures have emerged as powerful tools in the analysis of thoracic abnormalities. Despite their promise, several fundamental and practical challenges persist that hinder their clinical deployment.

Lung cancer lesions exhibit considerable variability in terms of size, shape, texture, and spatial location. This intrinsic heterogeneity complicates the design of generalizable deep learning models, particularly when trained on datasets that lack diversity in demographic, pathological, or imaging acquisition parameters. CNNs, while proficient at capturing local spatial features, often struggle with global context—an issue especially critical in tasks like tumor boundary detection and cancer staging. Attention mechanisms have been introduced in recent years to mitigate this limitation by enabling models to focus selectively on clinically relevant regions of interest, yet their integration with CNNs introduces additional architectural and computational complexity.

Furthermore, medical imaging data frequently suffer from low contrast, noise, and overlapping anatomical structures. This makes segmentation of tumors a highly non-trivial task. Deep learning models must not only localize suspicious regions accurately but also preserve semantic consistency across slices and modalities. In practice, these systems often face a trade-off between model complexity, inference time, and interpretability—each of which is critical in real-world diagnostic workflows.

In order to address these multifaceted challenges, this research aims to systematically investigate and design deep learning-based decision support frameworks that combine the spatial hierarchies learned by CNNs with the contextual reasoning power of attention modules. The goal is to enhance both classification accuracy and segmentation precision, thus contributing toward more reliable and interpretable lung cancer detection systems that can support early diagnosis and clinical decision-making.

Across all the image modalities such as chest X-rays, histopathological image, CT scans, the common challenge lies in developing deep learning systems that can generalize across diverse imaging characteristics, institutions, and patient populations. Effective solutions demand robust architectures [6][7] capable of capturing both local and global contextual information---often achieved through multi-scale CNNs, attention mechanisms, and modality-specific pre-processing strategies. Furthermore, training these models requires access to large, annotated datasets, which is often limited in the medical domain. This makes semi-supervised learning, domain adaptation, and data augmentation essential components of the overall system design.

This thesis utilizes the CT Scan Images and Histopathological images for developing deep learning based application for lung cancer detection. For the segmentation of lung regions, novel UNet variants are developed and evaluated, with the primary goal of enhancing the detection and delineation of small, irregular, and low-contrast nodules that are often missed by traditional methods. One of the conducted study explores advanced models such as R2UNet, which introduces recurrent residual connections to capture complex contextual features, and TransUNet, which leverages adaptive attention mechanisms to integrate both local and global dependencies within medical images. UNet architecture for lung CT image segmentation, was combined with recurrent residual UNet, traditional recurrent networks, and scSE modules. The model, R2UNet with scSE blocks, enhances depth to prevent vanishing gradients and improves pulmonary nodule detection. It uses recurrent residual and scSE blocks in the encoder, deconvolution layers in the decoder, and skip connections to preserve fine-grained spatial details.

Another methodology [8] that is BUS-UNet++, an ensemble model combining BUS-UNet and UNet++ for lung nodule segmentation was developed using the LIDC-IDRI dataset. The 68-layer architecture enhances feature extraction through deeper contracting paths and extensive skip connections between encoder, decoder, and aggregation blocks. It employs convolution, pooling, dropout, and batch normalization layers, with a bidirectional ConvLSTM for processing information in both directions, providing a novel framework for lung nodule segmentation.

While segmentation serves as the first step in lung image analysis, accurate classification of lung cancer images is equally critical for effective diagnosis and treatment planning. However, most existing studies in this domain rely heavily on deep convolutional neural networks (CNNs) without incorporating systematic feature selection strategies. This over-reliance on deep CNNs often leads to models that process large volumes of redundant or less informative features, thereby reducing efficiency and sometimes impairing classification accuracy.

A study was performed using ensemble deep learning models to classify the severity of lung nodules [9]. It integrates ResNet-152, DenseNet-169, and EfficientNet-B7 using a novel weight optimization method that combines ROC-AUC and F1 scores for automatic weight assignment. Evaluated on the LIDC-IDRI dataset, the model achieved 97.23% accuracy and 98.6% sensitivity, outperforming existing approaches and reducing false negatives.

Another ensemble model called the Mitscherlich Function-based Ensemble Network (MENet) [10] has been developed, which combines the prediction probabilities from three deep learning models—Xception, InceptionResNetV2, and MobileNetV2—to improve the accuracy of lung cancer prediction. The ensemble approach is based on the Mitscherlich function, which produces a fuzzy rank to merge the outputs of the base classifiers. The study was conducted using the publicly available Iraq-Oncology Teaching Hospital/National Center for Cancer Diseases (IQ-OTH/NCCD) lung CT scan dataset. The results demonstrated that the proposed method outperformed several state-of-the-art approaches across standard evaluation metrics.

The domain of histopathology-based lung cancer classification, in particular, has not extensively explored feature selection methods that could isolate the most discriminative features and enhance the learning process. To overcome these limitations, adaptive genetic algorithm–based feature selection strategy [11] has been developed. The feature extraction is performed using a CNN, where convolution and pooling layers act as feature extractors to learn complex image patterns, and the classifier uses these extracted features for final classification.

Future research in lung nodule segmentation can focus on several promising directions. There is a strong need for larger, ethically accessible medical datasets to improve model reliability and performance. Developing advanced and lightweight deep learning models will help handle complex data while enabling deployment in real-world, resource-limited settings. Semi-supervised and ensemble learning approaches can enhance segmentation accuracy by making better use of both labeled and unlabeled data.

Additionally, integrating explainable AI techniques can make these models more transparent and trustworthy for clinical use. The use of metaheuristic optimization methods, such as genetic algorithms or particle swarm optimization, could further refine segmentation accuracy. Combining multimodal data from CT scans, X-rays, and histopathology may lead to more comprehensive and personalized diagnosis. Finally, close collaboration between AI researchers and clinicians will be essential to ensure that technological advancements translate into meaningful improvements in patient care.

In conclusion, the conducted studies demonstrate the strong potential of deep learning in automating lung cancer detection, classification, and segmentation using medical imaging data. By integrating advanced architectures with ensemble learning strategies, the research achieved significant improvements in segmentation precision, classification accuracy, and overall model sensitivity, while effectively minimizing false negatives. The study also explored adaptive feature selection techniques to enhance model interpretability and reduce redundant information, leading to more efficient learning and reliable outcomes. Collectively, these efforts contribute toward building intelligent, data-driven diagnostic systems that can support radiologists in identifying lung abnormalities more accurately and consistently. The findings reaffirm that well-designed deep learning frameworks can play a crucial role in improving early diagnosis, optimizing clinical workflows, and ultimately enhancing patient care in lung cancer management.