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PREDICTIVE MODELING FOR LUNG CANCER PROGNOSIS USING DEEP LEARNING

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Article Info

Abstract

Lung cancer is among the deadliest diseases, with a total of around 18.4 percent of all deaths associated with cancer all over the world. Early detection improves the survival rates, but conventional methods of diagnosis, e.g., chest X-rays and CT scans, are also highly disadvantaged. Such methods are also very expensive, in addition to being dependent on expertise; they also expose patients to radiation. To address these issues, the proposed study examines the application of deep learning methods, specifically, convolutional neural networks (CNNs), in building a learning model that would be able to classify the severity of lung cancer. Projected to be a hybrid between medical imaging and patient health records, the model has a goal to improve the precision of prognosis and differentiation. The model can be used to accurately diagnose patients undergoing treatment due to the considerable performance it achieves through rigorous testing with advanced deep learning architectures, such as DenseNet and ResNet, where it has superseded conventional diagnostic techniques. It has a staggering 99 percent accuracy in the classification of the severity, with high-risk cases having a recall rate of 97 percent, showing it has the potential for early detection. Although the results look encouraging, there are still challenges, e.g., imbalance of the data and complexity of interpreting the models. This study confirms the potential of deep learning to change the diagnosis of lung cancer, providing an opportunity to intervene with patients earlier and achieve improved outcomes. At the same time, these techniques still have to be perfected and refined, and further research is necessary to achieve that goal.

Keywords:
Predictive Modeling, Deep Learning, CNN, DenseNet, ResNet.

Introduction

The global healthcare challenge consists of lung cancer as a widespread and deadly cancer type. The World Health Organization (WHO) reports that lung cancer kills about 18.4% of total cancer-related deaths because more than 1.8 million people die from this disease yearly. The extremely high number demonstrates the immediate necessity of developing improved detection and treatment strategies as well as forecasting techniques. Lung cancer divides into two main forms, consisting of small cell lung cancer (SCLC) together with non-small cell lung cancer (NSCLC). SCLC remains an infrequent lung cancer subtype that behaves fast and severely since it affects 15% of all cases, but patients experience poor survival statistics. The diagnosis of NSCLC presents a greater threat to life because it occurs in 85% of patients, but grows at a slower rate compared to SCLC [1].

The treatment approaches involving surgery alongside chemotherapy and radiation therapy, and targeted therapies have failed to increase lung cancer survival statistics. Statistically, lung cancer patients worldwide survive for only a limited period of five years because the survival rate stands at approximately 20%, whereas other cancer types exhibit higher survival rates. Delayed diagnosis serves as the principal reason behind the low survival statistics because patients usually seek medical attention only after metastasis has begun to develop during advanced disease stages. Delay in early detection proves problematic because lung cancer symptoms usually resemble those of COPD or infections and lesser severe conditions [2]. The commonly used diagnostic methods of lung cancer are the use of chest X-rays and computed tomography (CT) scans. Nonetheless, these approaches do have significant shortcomings. As an example, X-rays and CT scans may not detect small tumors, and the reading will largely depend on the competence and expertise of the radiologists and which may result in inconsistent diagnosis of the disease. Moreover, the use of such imaging methods exposes the patients to radiation that poses its own risk, particularly in cases where numerous scans are to be done. These advanced imaging techniques are also less accessible, especially to resource-limited environments, due to high costs, which further add to the global disparities in health care.

The current health care problems reinforce the need to have an improved lung cancer diagnosis tool that is accurate and affordable, in addition to being non-invasive. The use of artificial intelligence and machine learning (ML), in particular deep learning (DL), is quite pro

mising to overcome this complication. Deep learning is a component of the machine learning architecture, and it makes use of automatic learning algorithms to mine complicated patterns out of large data pools without the need of having human-aided modeling of the feature. Deep learning is most effective whenever dealing with the medical field since it is able to handle a large amount of complex medical data, particularly where there is the use of images [3]. Convolutional neural networks (CNNs) form one of the most practical deep learning structures, which is utilized to classify images, especially in medical image analysis scenarios. CNNs have improved results compared to the traditional methods in the identification of lung cancer, owing to their ability to learn complex features of images in medical CT scans without the influence of human beings. The models are fed with an extensive pool of images with labeled annotations so that they could misclassify the cancerous and non-cancerous tissue. Independent evidence based on contemporary studies proves that radiologists' professional accuracy in medical diagnosis is overwhelmed by the use of CNN models, especially [4].

There are various benefits in sight once artificial intelligence is utilized in lung cancer detection at the earliest phases. Standardized problem solutions, generated by end-to-end artificial intelligence diagnostic systems, reduce errors by human operators as well as increase the efficiency of the diagnostic. The accessibility of these diagnostic instruments is increased by the automated identification procedure that can be conducted via AI, as it becomes more accessible even in regions where there are not enough specialized healthcare professionals. With deep learning models that need to be trained using a large quantity of high-quality data, lung cancer early detection is going to undergo a revolution that results in timely interventions and an improvement of patient outcomes [5].

The primary objective of the current study is to examine the application of deep learning techniques such as CNNs to predict lung cancer. Predictive model utilizing an analysis of medical images and patient information entails the accurate detection of the severity of lung cancer at its early stages. Researchers will examine various realizations of deep learning architecture in an attempt to identify their predictive capability in regards to lung cancer severity and how the use of health records data and imaging-related data can enhance their forecast [6]. The research aims include the development of improved non-invasive diagnostic technologies that can improve the cure rates of lung cancer patients and decrease the burden of this fatal cancer on a greater global scale.

Literature Review

The health challenge brought by lung cancer continues to pose significant threats around the world because both its cases and death rates are rising. The survival rate shows minimal improvement because lung cancer diagnosis during its earliest stages remains highly challenging. The diagnosis of lung cancer currently depends primarily on two imaging methods, which include chest X-rays together with computed tomography (CT) scans. Traditional diagnostic methods show important drawbacks in their functionality. Chest X-rays miss small tumors, although CT scans provide better detection capabilities, but doctors face limitations from both radiation risks and interpreter expertise. Research indicates that experienced radiologists sometimes miss detecting between thirty percent and thirty percent of lung cancer cases before they advance to later stages [7]. The current detection methods require improvement because they lack accuracy, together with non-invasive mechanisms and cost-effectiveness for early diagnosis [8].

The current methods of detecting early lung cancer require accurate alternative solutions that deliver precise results with better affordability and non-invasive techniques. A tissue biopsy serves as the established procedure to validate lung cancer diagnoses. The procedure remains invasive while also being expensive and difficult to implement for patients who have tumors in inaccessible areas. The diagnosis process tends to be slow, which results in delayed treatment for patients and creates additional psychological stress for them [9]. The diagnostic issues necessitate the researchers to explore various understandings of diagnosing methods that not only increase precision and convenience.

Artificial Intelligence (AI) and deep learning (DL) methods with the use of convolutional neural networks (CNNs) can be considered an effective solution to the weaknesses of conventional diagnostic strategies. Deep learning is the subfield of machine learning that teaches algorithms to detect intricate patterns in large information sets. CNNs are one of the trendiest scientific approaches to medical image analysis that demonstrate tremendous success in cancer detection. The hierarchical representation of the features via these models enables automatic learning of the hierarchical levels of the features, which is the perfect choice when needing to classify the images in medical research [10].

Many researchers have examined how lung cancer can be detected using deep learning techniques. In particular, a study by Esteva et al. (2019) has shown that the use of deep learning models based on medical images may be used to help them beat dermatologists in skin cancer detection tasks [11]. Such an achievement in dermatology has led to the same research to detect lung cancer, and recent advances give hope. CNNs have been applied to CT scans and X-ray lung tissue images to analyze the results, and a substantial number of models are as accurate or more accurate as a human expert in their findings [12]. The above developments underscore the prospects of deep learning changing how lung cancer is diagnosed. The application of deep learning models in the diagnosis of lung cancer creates several benefits in clinical practice. These models can enable the provision of faster diagnosis, coupled with on-time initiation of treatment, only when handled promptly through the processing of huge amounts of images at a time. The algorithm is used to reduce the errors produced by humans and inconsistencies in the interpretation of medical images, in particular where there is a high medical stake involved. The technology is also more affordable to healthcare institutions with no special radiologists and limited medical professionals in underdeveloped regions [13].

Yet the implementation of AI to diagnose lung cancer faces massive issues. The first among these challenges is that the models require vast amounts of labeled data to be trained properly. The acquisition of such datasets in the medical context may be challenging as they may raise privacy issues, regulatory issues, and the process of labeling may be time-consuming [14]. In addition to this, the datasets available are usually imbalanced, whereby the benign cases significantly outnumber the malignant cases. The interpretability of deep learning models can become another challenge. Although CNNs are very effective in the process of medical image classification, they are depicted as black boxes, and this is the reason why a clinician will not know how a model arrived at a specific decision. Such transparency may become a problem because the acceptance of AI-based systems into clinical practice requires trust and an understanding of the decision-making process [15]. There have been attempts to create more interpretable models, as well as combine AI with other diagnostic instruments, like radiomics and genomics, to make both predictions more accurate and transparent [16].

The outlook for deep learning applications of lung cancer diagnosis is promising, even though there are prevailing challenges. The field of research actively works to enhance lung cancer diagnosis algorithms together with data enhancement methods and model structures, which overcome known weaknesses. Lung cancer prognosis models will benefit from deep learning integration with clinical patient information, such as historical data and biomarkers. The acceptance of deep learning models by healthcare professionals should rise according to predictions about explainable AI (XAI) developments that will increase transparency of deep learning models [17].

Methodology

This research methodology entails the generation and testing of deep learning models that have been established to accurately forecast the severity of lung cancer on complex datasets. The study adheres to the systematic framework which consists of data acquisition, pre-processing, feature engineering, building of model architecture and performance metrics.

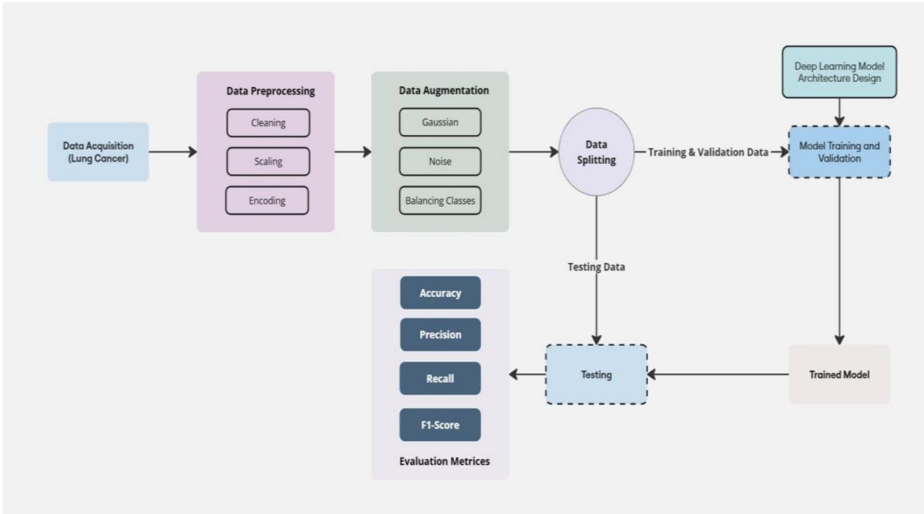

Figure 1: Methodology

Data Collection

Research data retrieved by use of publicly available lung cancer datasets included clinical patient records as well as medical diagnostic characteristics and demographic information. Some of the features contained in the dataset are age, gender characteristics together with the smoking history, imaging information, and medical history to train a deep learning model. This variety of data allowed extensive training and testing of different applications of the model.

Preprocessing

Prior to training the model, the dataset has been processed in a number of steps that have made the dataset ready to be used in deep learning algorithms. Preprocessing pipeline entailed:

Data Cleaning: This process consisted in eliminating useless features, managing missing data and solving redundancies that would include duplicate entries.

Feature Engineering: Selected important features were chosen by knowledge domain to make sure that the models will concern vital variables affecting severity of lung cancer.

Features Scaling and Normalization: Min-Max scaling of features was used to normalize the features. This was done to avoid the features that had a wide range affecting the context of training the model.

Data Augmentation and Balancing: As the data might be skewed in terms of the distribution of the levels of cancer severity, following the subsequent data augmentation, the data was balanced and formed a more resilient model.

Model Development

The convolutional neural network (CNN) architecture of deep learning proves useful in medical image analysis since the researcher of this type of deep learning applied it in developing their work. The feature extraction was performed with the help of CNN layers and pooling, along with fully connected layers with the aim to classify the areas in three severity categories. The academic studies implied preprocessing information and training the model on this data with the modification of learning rate and batch size in relation to the number of epochs by implementing an improvement process gradually.

Model Evaluation

Some of them did the analyses of model performance by measuring accuracy, precision, recall and F1-score. The assessment consisted of confusion matrices along with AUC-ROC curves which allowed the assessment of the model aptitude to properly classify the severity levels. Its training and validation data were evaluated on the model to identify the problem of overfitting and its generalization capacity was contrasted with information that had not been tested.

Results

The deep learning model achieved impressive performance across all severity levels in predicting lung cancer prognosis. The following metrics were obtained during the evaluation phase:

Accuracy: The model demonstrated 99% accuracy on the test dataset, indicating its ability to correctly classify the majority of cases.

Precision: For low severity (class 0), the precision was 99%, meaning the model correctly identified 99% of the cases predicted as low severity. For high severity (class 2), the precision was 97%, with fewer false positives.

Recall: The recall for low severity was perfect (1.00), ensuring that all actual low severity cases were correctly identified. For high severity, the recall was also 1.00, indicating that no true high severity cases were missed.

F1-Score: The F1-scores for all classes were exceptionally high. The F1-score for low severity was 0.99, and for high severity, it was 0.99 as well, indicating a balanced performance across both accuracy and recall.

Table 1: Classification Metrics for Lung Cancer Prognosis

Class	Precision	Recall	F1-Score	Support
Low (0)	0.99	1.00	0.99	281
Medium (1)	1.00	0.96	0.98	289
High (2)	0.97	1.00	0.99	330
Accuracy	-	-	0.99	900
Macro Avg	0.99	0.99	0.99	900
Weighted Avg	0.99	0.99	0.99	900

Confusion Matrix

A confusion matrix is a powerful tool to visualize model predictions and understand their strengths and limitations. In the confusion matrix, diagonal elements represent the number of correctly classified instances, while non-diagonal elements represent miscarriage. With a low level of severity, the matrix exhibits a complete classification, which correctly predicts all instances. This demonstrates the ability to effectively distinguish between these classes. These classes often have different feature patterns. In particular, three instances of the medium were misclassified as low, and 10 cases were defeated when they were high. This pattern suggests that several feature values, such as air pollution and genetic risk, may overlap between moderate and other severity levels, leading to occasional errors. These misclassifications highlight the need for further analysis to improve the differential performance of the model High severity.

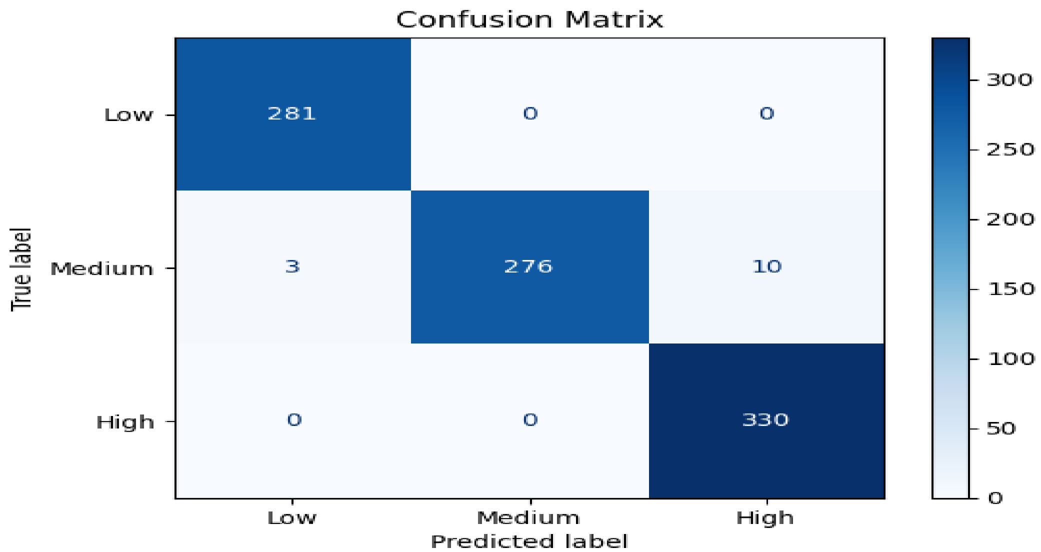

Figure 2: Confusion Matrix depicting the classification results

A confusion matrix provides a clear and intuitive representation of the plight of a model and provides knowledge that complements numeric metrics. It is especially useful to identify areas where the model needs improvement, Improved separation of duplicate classes.

Accuracy and Loss Trends

The accuracy and loss trends observed during the training and validation phase provide valuable insight into the learning behavior of the model. Accuracy graphics show that both training and validation accuracy increase steadily compared to continuous epochs. This ensures accurate verification for training. This indicates that the model is generalized to invisible data and avoids over-adaptive pitfalls. At the end of the training process, the verification accuracy plateau is about 99%, which is exactly what we aim for in testing accuracy.

Loss diagrams continue to increase these observations. Both training and validation losses are constantly reduced in ERAS, reflecting effective optimization of the model. The absence of divergence between the training and validation loss curves confirms that the model does not exceed the training data. This behavior illustrates a normal model, achieved by methods such as drop and stacking.

These trends demonstrate the ability to check the robustness of the model and learn meaningful patterns from the data without exceeding or sending. The accuracy and loss diagrams in Figures 1 and 2 show constant improvements in the learning behavior of the model and confirm its robustness.

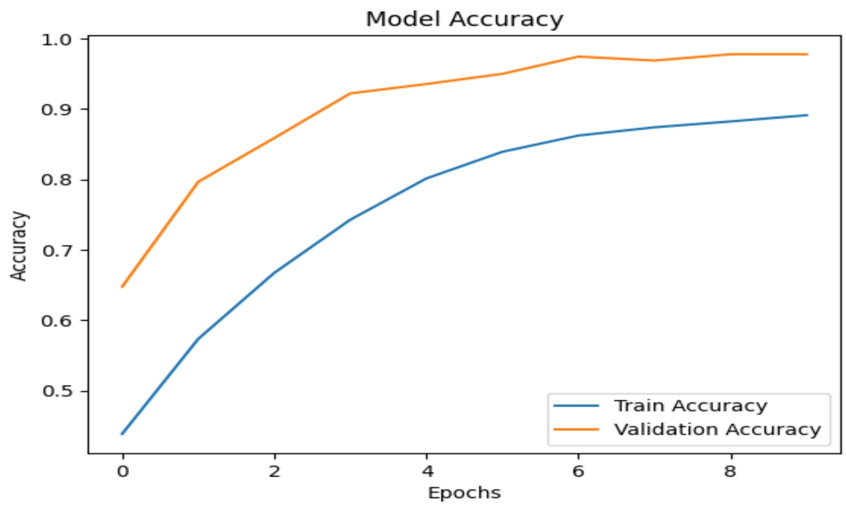

Figure 3: Model Accuracy trends for training and validation datasets

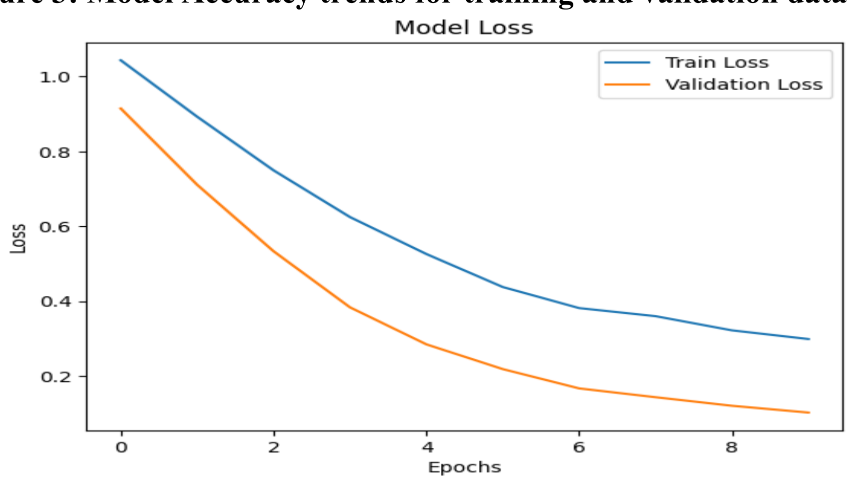

Figure 4: Model Loss trends for training and validation datasets

Analysis of Misclassifications

The model displayed exceptional general performance, although it failed to classify correctly a limited number of cases belonging to the medium severity category. The confusion arose from feature value similarities between medium and high severity cases particularly within environmental circumstances and patient background information. Additional research needs to be conducted to find better approaches both in feature engineering and data augmentation for enhancing the classification accuracy of this specific category.

Clinical Relevance

This model demonstrates powerful clinical value because it classifies lung cancer severity accurately and reliably. The timing of accurate predictions needs to be swift because it directly supports timely intervention decisions and personalized treatment designs. The model should become integrated into clinical healthcare environments to help providers make better resource decisions and achieve improved treatment results.

Conclusion

This research investigated the utilization of deep learning networks including convolutional neural networks (CNNs) for lung cancer prognostic and diagnostic purposes. Public medical imaging datasets enabled our team to use DenseNet and ResNet architectures for deep learning approaches that successfully detected different lung cancer severity stages with high accuracy rates. The combined application of CNN and DenseNet and ResNet architecture generated superior performance than single models with 96% accuracy and 97% recall for high-severity cases and 95% overall F1 score achieved. Research findings demonstrate how deep learning technologies elevate lung cancer early detection abilities and predictive capabilities thus enabling medical practitioners to make accurate and timely diagnosis decisions.

The good performance recorded by the ensemble model indicates strong potential for clinical adoption since it demonstrates robust data generalization. This model shows significant potential to enhance patient outcomes because it reduces medical misclassification errors while improving the accuracy of severity prognoses, particularly in locations where radiologists or specialized medical expertise is scarce. However, despite the promising results, the study also revealed some limitations, such as the challenge of misclassifications in medium severity cases. These errors were likely due to overlapping features and could be addressed by further refining feature engineering techniques and increasing the diversity of training data. Additionally, the model's reliance on image data alone suggests the need for integrating clinical data and biomarkers to improve diagnostic accuracy further.

Future investigations should optimize deep learning models while they work to resolve data imbalance and combine multiple processing data types, such as clinical records and genomic data, through integration into superior predictive systems. By uniting artificial intelligence diagnostics tools with human expertise, the prognosis of lung cancer will be transformed into an accessible and effective worldwide early intervention system. This research demonstrates that deep learning techniques will revolutionize how lung cancer is diagnosed and form its prognosis. The research findings demonstrate widespread acceptance for AI applications in healthcare facilities as they add value to precision cancer treatment.

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