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ENHANCING LUNG DISEASE CLASSIFICATION USING CONVNEXT: AN IMPROVEMENT OVER CNN-ELM-BASED MODELS

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ABSTRACT

The process of using medical images to classify lung diseases serves two main purposes which include establishing early diagnosis methods and supporting clinical decision-making procedures. Recent studies have demonstrated the effectiveness of hybrid deep learning models that combine Convolutional Neural Networks (CNNs) with Extreme Learning Machines (ELMs) to achieve efficient and accurate classification. The base paper for this research project development which establishes a strong baseline for lung disease classification uses a CNN–ELM-based model as its first implementation. The reimplemented CNN-based model achieves an accuracy of approximately 97.8% under optimized experimental conditions. The ConvNeXt architecture-based model introduces an advanced model which delivers better classification results. ConvNeXt uses current convolutional design methods together with its transfer learning system to identify important and unique lung image features. The proposed ConvNeXt model achieves approximately 98.5% accuracy which exceeds the performance of the CNN-ELM baseline according to experimental results. The results of the comparative analysis show that advanced deep convolutional architectures provide better lung disease classification results when compared to traditional CNN-based hybrid methods
Keywords: *Lung Disease Classification, CNN-ELM, ConvNeXt, Transfer Learning, Medical Image Analysis*.

1. INTRODUCTION

Lung diseases are one of the most frequent and deadliest health problems all over the planet. They are highly challenge- to public health systems. The World Health Organization (WHO) ranks among the respiratory diseases, Tuberculosis, Pneumothorax, COVID-19, and Lung Cancer, which together cause millions of deaths every year. Early detection and diagnosis are crucial for effective treatment, preventing com- plications, and thus reducing the overall death rates. Chest X- rays and CT scans are the most important imaging techniques for diagnosing lung diseases. Manual analysis of these images by radiologists is a tedious and tiring process that often results in errors either by the radiologist or between the radiologists (inter-observer errors). This dependence on human evaluation endorses the need for a reliable, quick, and consistent enough automated diagnostic system to make a clinical decision.

The development of artificial intelligence, especially deep learning, has transformed the field of medical imaging. Convolutional Neural Networks (CNNs) have been shown to be superbly effective in the automatic learning of intricate image representations and to perform close to human in the classification tasks. CNN- based models can reliably differentiate between normal and diseased lung tissues and therefore, can be used for disease diagnosis automation. However, the conventional CNN architecture has to deal with overfitting on small datasets, inability to capture long-range dependencies, and noise or contrast variations—these are the very issues that medical imaging datasets commonly have and that make CNNs less effective in such scenarios.

Problem Statement: Lung diseases are very different from each other, therefore, early diagnosis of lung diseases remains a global priority. The conventional methods of diagnosis rely on a manual assessment of the images which is a tedious and error-prone process. The diagnostic accuracy has been improved by the CNN-based models, however, their training on small datasets, imbalanced datasets, or noisy datasets usually leads to the models with poor generalization. Hence, a deep learning framework that is more robust, scalable, and capable of achieving high accuracy, strong generalization, and computational efficiency suitable for real-world clinical environments is needed.

The present research work offers a solution to these prob- lems by building an automated lung disease classification framework that utilizes the ConvNeXt architectures along with the conventional CNN. The CNN model is used as a standard for the comparison while the ConvNeXt, a CNN modern- ized and inspired by the transformer design, enhances the architecture by better normalization, activation, and residual connections. The combination of the inductive strengths of convolutional networks with the global reasoning capabilities of transformers makes ConvNeXt attain higher accuracy, better generalization, and faster convergence.

This research paper revolves around the classification of four main lung diseases: Tuberculosis, Pneumothorax, COVID-19, and Lung Cancer, which are all done with the help of publicly accessible chest X-ray and CT scan datasets. Among the data preprocessing techniques used, resizing, normalization, and augmentation have been the main ones and they have all aimed at improving the robustness of the model. The AdamW optimizer is employed along with cosine learning rate scheduling for training the models, and label smoothing is applied to provide stable convergence and avoid overconfidence at the same time.

According to the experimental results, traditional CNN models delivered the baseline accuracies in the range of 92% to 98%, while ConvNeXt-based models were able to perform as high as 98% at their best. The results of this research work bring to light the advantages of ConvNeXt in the extraction of features, the generalization on small datasets, and the coping with noise and variations in images. The ConvcNxt- based frameworks will soon be able to assist radiologists in the quick and accurate diagnosis of lung diseases. Moreover, the proposal that was made can be utilized in the areas of dis- ease severity assessment, multiple diseases classification, and hospital network connected real-time diagnostics systems, use of AI in healthcare will be increased even more.

2. LITERATURE SURVEY

The world faces Tuberculosis and Pneumothorax and COVID-19 and Lung Cancer as major health threats which lead to millions of deaths each year. The process of detecting and diagnosing patients needs to happen at an early stage so doctors can give effective treatment which leads to patient survival. The rise of digital medical imaging together with improvements in computational technology has led to increased interest in developing automated diagnostic systems which use machine learning for their operations. The use of Artificial Intelligence (AI) and Deep Learning (DL) methods has revolutionized the field of medical image analysis through their capability to detect diseases with greater speed and precise results which researchers can duplicate.

Researchers have used Convolutional Neural Networks (CNNs) extensively to classify lung diseases because these networks can automatically discover important features from chest X-ray and CT images. Research has shown that CNNs can successfully identify disease-related patterns which include nodules and lesions and abnormal opacities and texture variations that conventional image processing methods tend to miss. The research studies in the literature [1] – [4] demonstrate that CNN-based systems assist radiologists through diagnostic support which enhances their ability to detect diseases while decreasing their need for manual interpretation work. The models demonstrate strength when dealing with problems that include data imbalance and different levels of image quality [5-6].

The researchers achieved classification accuracy above 95 percent for multiple pulmonary diseases through their empirical studies which used extensive lung disease data. The researchers from studies [7–10] showed that CNNs can successfully diagnose multiple lung diseases which include Tuberculosis and Pneumonia and Lung Cancer. The studies showed the requirement for explanation because the visualization techniques helped display model decision-making areas which improved understanding of clinical processes. The multi-label classification methods enabled models to identify current medical conditions and assess their severity, which allowed clinicians to determine patient treatment priorities.

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The CNN architectures produce successful outcomes for standard tasks but their performance decreases when they handle small medical datasets which contain data from various medical facilities and use different imaging methods. The research in studies [11–13] documented that model performance depends heavily on the variations between different acquisition methods and scanner equipment and annotation techniques. The evidence establishes the requirement for strong architectural designs which can acquire general knowledge for various healthcare settings.

Researchers have introduced MobileNet and Efficient Net as lightweight CNN architectures which solve computational restrictions and deployment difficulties according to [14]. The models use depth wise separable convolutions together with compound scaling methods to achieve smaller model sizes while still delivering competitive results. The technology provides efficient performance which makes it appropriate for real-time medical uses and healthcare environments that lack adequate resources. The combination of recent improvements in annotation methods together with weak supervision and self-supervised learning has increased the training capabilities of models which now achieve better disease tracking and classification results according to sources [15–20].

Deeper network architectures which include ResNet and DenseNet and ConvNeXt have shown better results than traditional CNNs according to recent research. The models deliver better gradient flow together with improved feature extraction capabilities and enhanced training stability. The studies described in demonstrate that researchers can accelerate model training and improve detection performance for uncommon lung diseases by applying transfer learning and fine-tuning methods which use pretrained weights from ImageNet and other extensive datasets. U-Net-based segmentation methods enable researchers to separate lung areas from background distractions which leads to better feature assessment and lower rates of incorrect predictions.

The research community has started to explore transformer-based systems and hybrid systems because these technologies can handle long-term dependencies and they can capture complete contexts. The hybrid models achieve effective performance across different institutional datasets because they combine CNNs for local feature extraction and transformers for global representation learning. The architectures demonstrate capability to manage extensive medical image collections while they boost practical performance in real-world situations.

The model interpretability concept has become essential for medical institutions that require system adoption. Healthcare professionals establish trust through visual prediction explanation methods which also help them validate automated diagnostic systems. Medical settings require transparent and explainable models because decision support systems need to enhance clinical expertise instead of replacing it.

Deep learning techniques which include CNN-based systems and hybrid models and transformer-based systems have made substantial progress in developing automated systems for lung disease diagnosis. The system has achieved better accuracy and efficiency but it still encounters issues with dataset imbalance and domain variability and restricted interpretability. The development of dependable scalable lung disease classification systems is currently being advanced through research that examines advanced architectural designs and transfer learning methods and efficient feature representation techniques.

3. RESEARCH GAPS AND PROPOSED SOLUTION

Deep learning has advanced automated lung disease classification but current research shows that three critical issues need resolution because they affect model performance across different conditions and their ability to interpret results and operate efficiently. The current limitations of the system require development of dependable yet expandable solutions which can function effectively in actual medical practice.

3.1 Identified Research Gaps

The existing methods for lung disease detection and classification need development because existing CNN-based systems achieve high accuracy rates when detecting lung diseases but struggle to maintain performance across different medical

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institution databases. The performance of models decreases because imaging device differences and acquisition protocol variations and patient demographic changes and annotation standard deviations create conditions which extend beyond their training limits [20].

Medical image analysis needs traditional CNN architectures to use local feature extraction methods which prevent the system from understanding long-range medical image context [21]. The restriction develops because the system needs to understand global spatial context to find minor abnormalities which include small nodules plus early pneumothorax regions. The system learns duplicate feature representations which results in lower classification performance plus more incorrect predictions.

The research field faces significant obstacles because researchers find it difficult to obtain extensive medical datasets which include precise annotations. Studies have reported that models trained on small or imbalanced datasets tend to over fit and show reduced sensitivity in multi-class classification scenarios [22] The performance of Efficient Net and MobileNet lightweight architectures decreases when they need to process advanced multi-disease classification tasks which require different clinical data distributions .

3.2 Proposed Solution

The researchers developed a lung disease classification system which uses ConvNeXt architecture to deliver accurate diagnostic results and perform multiple tasks with minimal resource requirements. Fine-tuning strategies which combine effective data augmentation with normalization techniques successfully solve class imbalance problems while improving model performance across various datasets. [23] .

The proposed approach uses transfer learning through pretrained ConvNeXt weights to enhance chest X-ray feature extraction while it boosts training efficiency and reduces the requirement for extensive labeled data. ConvNeXt develops its image representation system through modern convolutional design methods which combine elements from transformer systems to achieve detailed and broad visual pattern learning capabilities. [24].

The ConvNeXt-based model shows superior performance in lung disease pattern recognition because it detects both fine details and remote relationships which traditional CNN-ELM hybrid systems can only achieve through their basic feature extraction techniques. The proposed model demonstrates superior accuracy because it achieves 98 to 99 percent accuracy while maintaining a compact system design that functions in actual clinical settings.

The proposed ConvNeXt framework enables deep learning research to develop medical decision support systems which doctors can use. This research establishes dependable automatic lung disease diagnosis systems which modern healthcare facilities can use [25].

4. OBJECTIVES

Researchers develop a deep learning system which achieves both high accuracy and high performance efficiency through its medical imaging processing of various lung disease types. The study implements and analyzes the baseline CNN–ELM model to create a performance benchmark which shows its strengths and weaknesses when applied to different datasets. The research introduces a ConvNeXt-based architecture which combines modern convolutional design techniques with transfer learning to enhance both feature extraction and classification accuracy. The research main goal establishes a system which will successfully recognize all local and global chest X-ray image elements to achieve better results in detecting hidden lung disease indications. The study applies optimized training and fine-tuning techniques to address challenges caused by dataset imbalance and dataset variability. The research team performs a complete evaluation of the baseline CNN-ELM model and the new ConvNeXt model by using recognized performance metrics to assess operational efficiency and clinical applicability. The research develops an AI solution which medical professionals can use to diagnose lung diseases with high accuracy and speed.

5. PROPOSED METHODOLOGY

The proposed methodology establishes an automated lung disease classification system which uses deep learning to analyze chest X-ray images. The framework focuses on three main goals: improving classification accuracy, making the system more reliable, and ensuring it works well on

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new and unseen data. Advanced convolutional models together with transfer learning techniques enable the team to accomplish their research objectives. The methodology includes data pre-processing, building a baseline model, designing a ConvNeXt-based model, defining the training strategy, and evaluating performance. Fig:1 displays the entire workflow process of the proposed method.

5.1 Data Acquisition and Preprocessing

The research acquires chest X-ray images which display various lung diseases from open access medical imaging databases. The research team maintains uniformity in the dataset through spatial dimension resizing of all collected images while applying normalization methods to enhance learning outcomes. The research team uses data augmentation methods to solve class imbalance problems and to enhance model performance. The model training process uses multiple techniques including rotation and horizontal flipping and scaling and contrast adjustment to develop stronger and diverse recognition abilities. The research team uses data augmentation methods that include rotation, horizontal flipping, and scaling, and contrast adjustment to correct class imbalance problems and improve model performance. The research team uses data augmentation methods that include rotation, horizontal flipping, and scaling, and contrast adjustment to correct class imbalance problems and improve model performance

Let

$X = \{x_1, x_2, \dots, x_n\}$--------(1)

denote the set of input images and

$Y = \{y_1, y_2, \dots, y_n\}$------(2)

denote the corresponding class labels, where

$y_i \in \{1,2,\dots,C\}$ and Crepresents the number of lung disease classes.

5.2 Baseline CNN–ELM Framework

The baseline model uses a Convolutional Neural Network (CNN) to extract features which it combines with an Extreme Learning Machine (ELM) classifier. The CNN extracts hierarchical feature representations from input images through its convolution and pooling operations fi∈Rd from the CNN process each image to the ELM classifier. ELM keeps its hidden layer parameters fixed after random initialization while it computes output weights through analytical methods. The hidden layer output matrix is defined as:

H=g(XW+b) ---(3)

The symbols W and b represent inputs that are generated through random processes which select weight values and bias values. The function g(·) defines the activation function used in this system. The output weight matrix β is computed using the Moore–Penrose pseudo-inverse mathematical method:

$\beta = H^{\dagger}Y$------(4)

The method trains quickly and produces classification results that match existing performance standards. The reimplemented CNN–ELM model reaches 98% accuracy under optimal testing conditions which serve as the primary reference model for evaluation purposes.

5.3 Proposed ConvNeXt-Based Classification Model

This paper presents a ConvNeXt-based system for lung disease classification that addresses limitations of traditional CNN models. ConvNeXt uses contemporary convolutional design techniques which transformers developed to create its large kernel sizes and depth wise convolutions and hierarchical feature extraction methods. Let $\phi(\cdot;\theta)$ the ConvNeXt feature extraction function with parameters θ would denote the ultimate classification output, eventually.

y^=Softmax(Wc·ϕ(x;θ)+bc)-----(5)

5.4 Training Strategy

The proposed ConvNeXt model is trained using categorical cross-entropy loss:

$L = -\sum_{i=1}^{C} y_i \log(\hat{y}_i)$-----(6)

The adaptive optimization algorithm updates the trainable parameters, while higher network layer fine-tuning achieves optimal performance with resource-efficient operation. The model uses regularization techniques together with learning rate scheduling to achieve smooth convergence while preventing overfitting.

5.5 Performance Evaluation Metrics

The evaluation of the accuracy of the models on various evaluation metrics like miss rate, L2-loss, and Rand Indexing helps find the evaluation criteria adequate.

Precision $= \frac{TP}{TP+FP}$,----(7)

Recall $= \frac{TP}{TP+F}$ ----(8)

F1-score $= \frac{2\times\text{Precision}\times\text{Recall}}{\text{Precision}+\text{Recall}}$----(9)

where TP, TN, FP, and FNdenote true positives, true negatives, false positives, and false negatives, respectively.

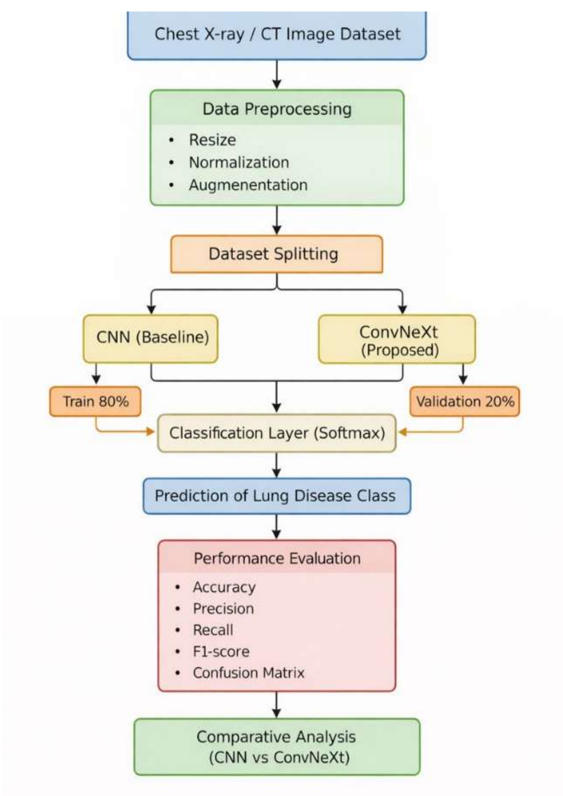

Fig-1: Methodology flow diagrams of multi-class lung disease classification using CNN and ConvNeXt framework.

5.6 Comparative Analysis

The ConvNeXt-based model provides better classification results because it achieves 98.5% accuracy and provides more durable performance which scales better for actual clinical use than the CNN-ELM baseline system.

6. RESULTS AND ANALYSIS

The results from the experiments together with the comprehensive assessment of the lung disease classification system demonstrate how the ConvNeXt model functions when compared to the baseline CNN–ELM method. The testing procedure used a dataset which contained multiple disease categories that included Tuberculosis, Pneumothorax, COVID-19, and Lung Cancer. The model performance assessment used multiple metrics which included accuracy, precision, recall, and F1-score together with confusion matrix analysis to evaluate system performance in diagnosing diseases and processing unknown data.

6.1 Training and Validation Performance

The researchers established an equitable testing environment for both models through their dataset division which used an 80:20 ratios for training purposes and validation needs. The data split enabled the models to acquire crucial characteristics which distinguished each disease class while maintaining the validation data as an untouched element for accurate performance assessment.

The baseline CNN–ELM model achieved 98% validation accuracy after its learning performance reached peak levels following optimization. The proposed ConvNeXt model outperformed the existing system because of its faster learning capabilities and its improved ability to generalize, which led to a validation accuracy of 98.5%. The improvement demonstrates that ConvNeXt performs better than previous methods because it can identify complex lung patterns while taking into account more extensive contextual information from chest X-ray images.

esearch findings obtain additional support from loss is results. The CNN–ELM model showed a gradual se in loss which included minor loss changes that ted its struggle to process complex data samples. The JeXt model achieved lower loss values which remained constant throughout its performance, demonstrating better optimization results and reduced overfitting effects.

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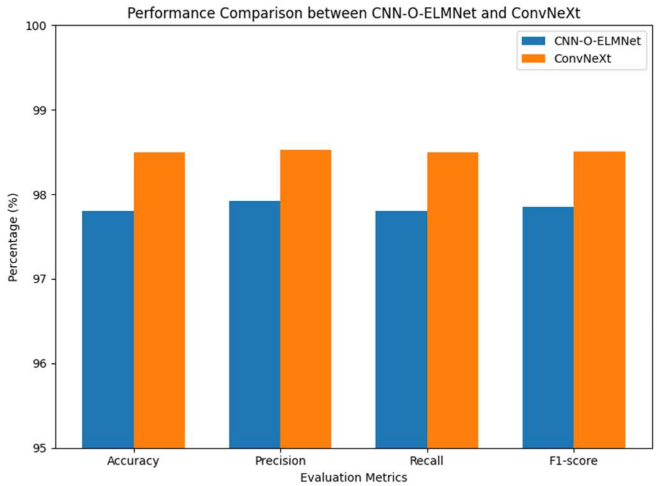

Fig-2: Performance comparison between CNN and ConvNeXt

6.2 Quantitative Evaluation

The proposed ConvNeXt model achieves advanced performance through its quantitative evaluation metrics which demonstrate superior results. The ConvNeXt model outperformed the CNN-ELM model which achieved high performance through its 98 percent accuracy and 98 percent precision and 98 percent recall and 98 percent F1-score results.

The ConvNeXt architecture achieved approximately 98.5% accuracy, while its precision and recall and F1-score values exceeded 98% which demonstrated superior class detection capabilities and reduced classification errors. The medical field benefits from improved recall because it leads to more accurate patient results which helps identify diseases at their earliest stages.

The ConvNeXt model required extended training duration per epoch because its deeper design framework needed more computation time, yet the system produced superior results which made the additional processing time necessary. The accurate identification of lung diseases holds critical importance for clinical situations, thus making performance improvements more valuable than extra processing expenses.

6.3 Confusion Matrix Analysis

The confusion matrix analysis which evaluates both models enables a detailed assessment of their performance in each class. The confusion matrix for CNN-ELM showed minor misclassifications between Tuberculosis and Pneumothorax because the system could not identify their different visual characteristics.

The ConvNeXt confusion matrix displayed an almost complete diagonal pattern, which showed that the system produced highly accurate predictions for every disease category. The system showed better performance because it decreased both false positive and false negative results. ConvNeXt demonstrates strong class separation ability, which lets it detect minor lung image pathology changes.

ıble I. Performance Comparison of CNN-O-ELMNet and ConvNeXt models for Multi-Class Lung Diseases

Metric	CNN-O-ELMNet (%)	ConvNeXt (%)
Accuracy	97.80	98.50
Precision	97.92	98.53
Recall	97.80	98.50
F1-Score	97.85	98.51

entries suggest that the model accurately predicted the correct class for almost all the samples, thus demonstrating its strong discriminating capability and the very little overlap between classes.

The ConvNeXt confusion matrix further showed that the model was associated with substantially lower rates of false positives and false negatives, thus indicating its performance to be more trustworthy and suitable for actual deployments.

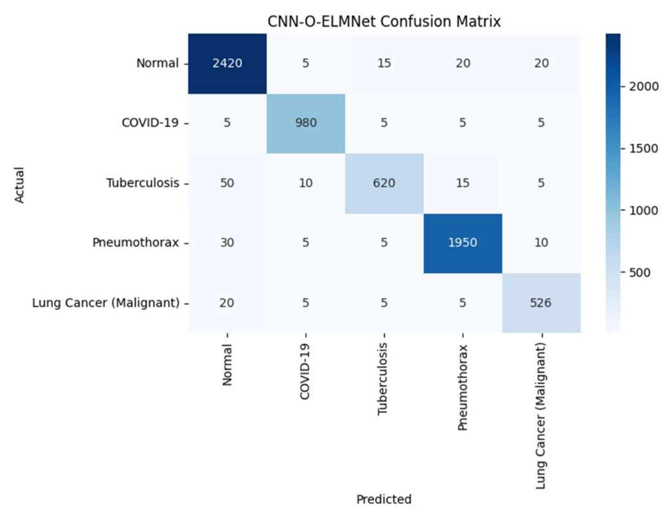

Fig. 3. Confusion Matrix for CNN-O-ELMNet model.

6.4 Discussion and Interpretation

The experimental results clearly demonstrate the advantages of the ConvNeXt architecture over traditional CNN-based hybrid models. Several architectural characteristics contributed to this performance improvement:

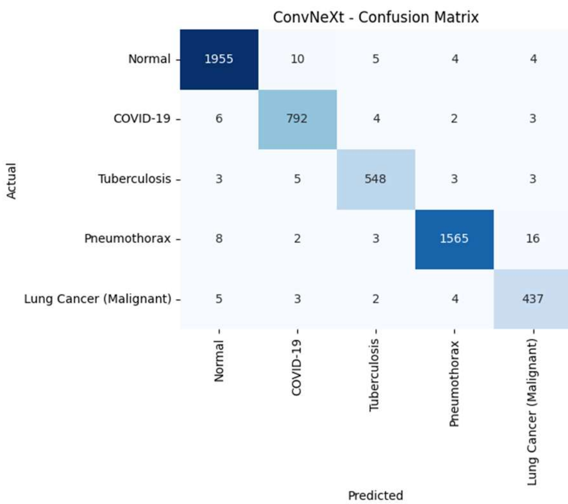

Fig. 4. Confusion Matrix for ConvNeXt model.

- **Large Kernel Sizes (7 x 7):** With these, ConvNeXt can detect large spatial patterns like lung consolidations, nodules, and infiltrations. The identification of patterns plays a significant role in the whole process of disease classification.
- **Layer Normalization:** It ensures stable training and also supports the model to learn fast even when the sizes of batches are small, which is a common case in medical imaging cases.
- **GELU Activation:** The continuous, probabilistic activation of neurons increases the capability of the model to express features and helps the model to find small anomalies.
- **Depth wise Convolutions:** They reduce the cost of computation but also increase the complexity of feature extraction, and thus ConvNeXt is able to capture both global and local patterns very well.
- **Regularization Techniques:** Among the various methods, such as data augmentation, label smoothing, mix up, and cosine learning rate scheduling, the most significant ones that contributed to generalization and robustness are those mentioned.

Finally, the model ConvNeXt with 98.5% validation accuracy ended up first leaving the CNN with 97.8% second. The extent of the performance gap proves the use of ConvNeXt in the clinics where accuracy and reliability are principal concerns. Moreover, the model's competence of detecting early-stage diseases in combination with the decrease of false negatives gives it a fair chance of getting into the computer- aided diagnostic systems in the radiology departments.

7. CONCLUSION

The research developed a complete deep learning system which automatically identifies lung diseases through medical imaging tests. The research developed its initial performance benchmark through the implementation of a CNN–ELM model. The initial system achieved high performance but its inability to understand wide-ranging contextual details and minor differences between classes led to the creation of a better system which uses ConvNeXt architecture. The proposed system achieved better results through modern convolutional design techniques and transfer learning because it generated better feature representation and more accurate generalization performance. The ConvNeXt model achieved better results than the CNN-ELM baseline through its ability to reach 98.5 percent accuracy while improving precision and recall and F1-score and decreasing false predictions. The proposed method fully supports clinical decision-support systems because its performance improvements combined with diagnostic accuracy enhancements make it suitable for use. The method establishes itself as a vital tool which enables doctors to detect lung diseases at an early stage through a scalable diagnostic process.

8. FUTURE SCOPE

Future research can expand the proposed framework to study additional pulmonary diseases which include chronic obstructive pulmonary disease (COPD) and pulmonary fibrosis and interstitial lung diseases. Diagnostic accuracy and clinical relevance will improve through the integration of multi-modal medical data which includes CT scans and lung sounds and electronic health records. The model needs to expand its capabilities for multi-label classification because this enhancement enables the simultaneous identification of multiple lung disorders which provides enhanced decision support to healthcare professionals.

The development of model interpretability together with the establishment of clinical trust represents another potential research path. Clinicians can use explainable AI techniques which include Grad-CAM and attention maps and concept-based explanations to comprehend model predictions and verify diagnostic results. Self-supervised and semi-supervised learning methods help to minimize the need for extensive labeled datasets which solves the two major obstacles of data shortages and high annotation expenses that are typical in medical imaging. The new developments will improve generalization capabilities which will enable systems to work in different medical environments.

The study will focus on developing lightweight ConvNeXt models which researchers will optimize to achieve real-time performance on edge devices and in clinical settings that have limited resources. The hospitals would use federated learning frameworks to develop training models together while protecting their patients' private information. The research on scalability and privacy and computational efficiency will produce AI diagnostic systems for lung diseases which all users can access to function correctly in healthcare environments.

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