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Classification of Lung Nodules as Benign or Malignant Using Convolutional Neural Network with Long Short-Term Memory

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Abstract— ***Lung cancer's significant global burden underscores the need for effective early detection methods, which are often challenged by complex tumor patterns. This research provides an advanced detection method that combines Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM) networks to overcome these issues. The proposed hybrid architecture integrates deep learning along with image processing and data augmentation techniques to enhance both accuracy and generalization. In this approach, CNNs extract essential spatial information from lung CT scans, while LSTMs collect temporal connections which improves the model's overall performance. The model achieves an impressive 92.4% accuracy, showing major advances in lung cancer detection and the possibility for better patient outcomes through more accurate and reliable diagnostic capabilities.***

Index Terms— ***Deep Learning, Benign, CNN, CNN-LSTM, Malignant, Lung cancer classification.***

I. INTRODUCTION

Brain tumors are aberrant cells in the brain, Lung cancer ranks as the top cause of cancer mortality worldwide [1], due to its late discovery and difficulties recognizing early-stage malignancies. Early diagnosis is essential for better treatment of patients, but established diagnostic approaches sometimes struggle with the specific characteristics of early malignancies and the variety in tumor patterns. Lung nodules, which are small growths in the lung, are important indicators of potential lung cancer. Differentiating between benign and malignant nodules is essential but challenging with conventional imaging methods like CT scans, which produce vast amounts of complex data. Recent advances in deep learning provide intriguing prospects. Convolutional Neural Networks (CNNs) proved significant potential for evaluating CT scans by collecting complicated information. However, CNNs may not capture all of the temporal and sequential complexities in the data. To address this challenge, hybrid models integrating CNNs with Long Short-Term Memory (LSTM) networks have been developed. LSTMs are adept at recognizing sequential patterns and temporal dependencies, complementing CNNs and enhancing diagnostic accuracy.

This research presents a combined CNN-LSTM architecture aimed at enhancing the classification of lung nodules and improving cancer detection. By integrating this method with image processing and data augmentation techniques, The model is designed to deliver improved accuracy and generalization in comparison to conventional CNN approaches. We evaluate its performance and compare it with standalone CNN models, proving its ability to improve early lung cancer diagnosis and patient outcomes.

The paper is organized as follows: Section II reviews relevant works, Section III details the proposed methodology, Section IV presents the results and discussion, and Section V offers the conclusions.

II. RELEVANT WORKS

Study [2] highlights the promise of Convolutional Neural Networks (CNNs) in enhancing lung cancer diagnosis from CT images, though specific accuracy metrics are not detailed. Research [3] advocates for deep learning applications in lung cancer detection, noting opportunities to address challenges related to overfitting and generalization. Study [5] demonstrates a 73% classification accuracy using a 2D CNN for nodule classification, showing promise but limited by its focus on small nodules and preliminary nature. Research [7] explores the use of 3D neural networks for lung nodule diagnosis, emphasizing the balance between accuracy, advanced design, and practical implementation, but it does not thoroughly analyze specific drawbacks. Study [9] employs Pylidc to segment CT images from the LIDC-IDRI dataset, manually classifying them as benign or malignant. While the study trains an LSTM model on 791 pulmonary nodule images, it faces challenges in managing complex spatial data to enhance classification accuracy. Research [10] introduces MBEL-3DCNN, a novel approach combining a 3D CNN with a Multi-Branch architecture and Ensemble Learning to address false positives and accommodate nodule variability, achieving a sensitivity of 72.9%. Study [12] highlights the role of CT scans in early lung cancer detection, showing CNN-based methods can achieve a high accuracy of 90.85%. Meanwhile, [18] reports an 84.40% accuracy with a

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deep hierarchical semantic CNN for predicting nodule malignancy, but notes that the lack of domain expertise for fine-tuning could limit accuracy in complex scenarios, suggesting that expert input could further improve results.

III. METHODLOGY

This study proposes a deep learning framework for classifying lung nodules from CT scans, focusing on enhancing detection accuracy. The methodology involves preprocessing and augmenting CT scan images to ensure high-quality input for model training. Figure 1 depicts the system architecture that merges Convolutional Neural Networks (CNNs) for extracting spatial features with Long Short-Term Memory (LSTM) networks to model temporal relationships. This integrated CNN-LSTM framework enhances the classification of lung nodules by using both spatial and sequential information. The approach is rigorously evaluated using training, validation, and test datasets to assess its performance in distinguishing between benign and malignant nodules.

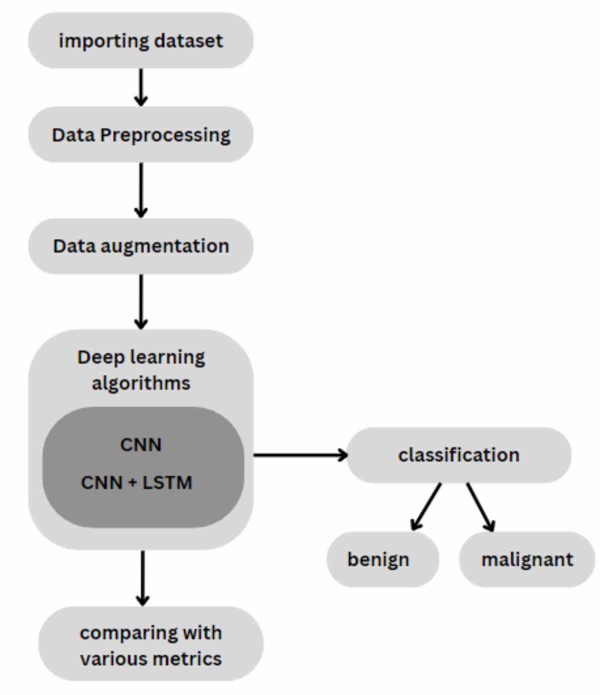

Fig. 1. Proposed Architecture

A. Pre-Processing

In the proposed system, preprocessing techniques such as image resizing and normalization are employed. Specifically, images are resized to 224x224 pixels. Reducing the pixel count not only standardizes the input size throughout the dataset, but also reduces the number of input nodes in the neural network, lowering model complexity and training time. Normalization is an important step in the preprocessing pipeline. This method normalizes the pixel values of the image to a consistent range, ensuring that feature values are aligned on a consistent scale. This step is essential for improving data analysis, enhancing the accuracy of the model, and minimizing discrepancies that may arise due to varying feature scales across different images. These steps guarantee that the input data given into the model is clean, uniform, and ideal for training, thereby contributing to the overall effectiveness and accuracy of the lung nodule classification process.

B. Data augmentation

To enhance the diversity and robustness of the lung imaging dataset, a data augmentation pipeline was implemented using TensorFlow’s Image Data Generator. The augmentation techniques included pixel rescaling, rotations up to 20 degrees, 20% width and height changes, and zooming by 20%. Additionally, horizontal and vertical flips were applied to boost the variability of the training data. This augmentation technique was utilized for both the training and validation datasets, providing the model with diverse scenarios during training. By incorporating these augmentations, the model became more capable of generalizing across different orientations and variations in lung nodules, ultimately improving its accuracy and robustness in real-world applications.

C. Deep Learning Algorithms

In lung cancer diagnosis, accurately classifying images into categories such as normal, malignant, and benign is crucial. This paper presents an advanced deep learning approach that enhances classification accuracy by leveraging the strengths of CNNs for spatial data processing and LSTM networks for capturing sequential dependencies.

Convolutional neural network (CNN)

CNNs, or Convolutional Neural Networks, are utilized for their proficiency in handling image data through a series of convolutional operations.

Convolutional Layers: The model starts with two Conv2D layers, each of which uses ReLU activation to extract spatial characteristics from the images.

MaxPooling Layers: Following each Conv2D layer, MaxPooling2D layers are used to reduce spatial dimensions.

Flattening and Dense Layers: The feature maps produced are converted into a one-dimensional vector. This vector is then processed through fully connected Dense layers, each comprising 128 neurons, utilizing ReLU activation and dropout techniques to mitigate overfitting.

Output Layer: The concluding Dense layer, equipped with a softmax activation function, classifies the input into three distinct categories: benign, malignant, and normal.

Compilation and Training: Adam's optimizer was used to compile the model.

Hybrid CNN with Long Short-Term Memory (LSTM):

Long Short-Term Memory (LSTM) networks, a specialized form of recurrent neural networks, are adept at

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maintaining information over sequences, making them well-suited for tasks involving temporal patterns. When integrated with Convolutional Neural Networks (CNNs), which excel in spatial feature extraction, the LSTM layer enhances the model's ability to analyze sequential features.

Convolutional Layers: The initial CNN phase use the TimeDistributed wrapper to perform Conv2D operations at each stage in the input sequence. The first Conv2D layer extracts spatial characteristics from each picture by using 256 filters, a 3x3 convolutional kernel, and activated using ReLU. To lower spatial dimensions, a MaxPooling2D layer with a 2x2 pooling window is applied next. Additional Conv2D and MaxPooling2D layers further refine the feature extraction.

Flattening and LSTM: For each time step, the two-dimensional feature maps are flattened into a one-dimensional vector, which is then passed through the LSTM layer for further processing, which consists of 100 units. The LSTM layer captures temporal dependencies from the sequence and outputs only the final state (return_sequences=False).

Fully Connected Dense Layers: The model concludes with a dense layer consisting of three neurons, followed by a softmax activation function. This final layer provides probabilistic classifications for the categories: benign, malignant, or normal.

Compilation and Training: The model is constructed using the Adam optimizer and categorical cross-entropy loss function, ideal for multi-class classification tasks. The training process utilizes sequences of medical images, optimizing parameters across multiple epochs to learn both spatial and temporal elements.

Figure 2 presents the CNN-LSTM architecture employed in this study, providing a visual representation of the combined model structure and flow.

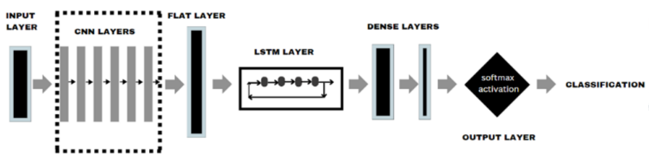

Fig. 2. CNN-LSTM model architecture

IV. RESULTS AND EVALUATION

The dataset in this study includes 1,097 lung CT images, partitioned into training and validation sets with an 80:20 split. This technique assures a full training process and provides a robust evaluation of model performance.

A. Performance Evaluation

The CNN and CNN-LSTM algorithms were trained for 20 epochs each. Table 1 summarizes the performance metrics for each model.

Table I: Comparing CNN-LSTM with CNN

Performance Measure	CNN-LSTM model	CNN model
Accuracy	0.9246	0.6495
Precision	0.9272	0.7740
Recall	0.9242	0.4749
specificity	0.9637	0.9166
sensitivity	0.9242	0.4749

Accuracy: The CNN-LSTM model attained an accuracy of 0.9246, representing a notable improvement over the CNN model's accuracy of 0.6495. This shows that the CNN-LSTM model accurately classifies lung nodules more frequently, making it a more reliable model overall.

Precision: With a precision of 0.9272, the CNN-LSTM model exceeds the CNN model, which has a precision of 0.7740. Higher precision means the CNN-LSTM model is more accurate in its positive predictions, thereby reducing the number of false positives and improving its effectiveness in identifying true positives.

Recall: The CNN-LSTM model has a recall of 0.9242, significantly greater than the CNN model's 0.4749. This illustrates that the CNN-LSTM algorithm detects a bigger proportion of genuine positives, which is critical for medical diagnostics. Missing a true positive might have serious consequences.

Specificity: The CNN-LSTM model exhibits a specificity of 0.9637, compared to 0.9166 for the CNN model. Higher specificity suggests that the CNN-LSTM framework is better at properly recognizing negative instances and minimizing false positives, hence improving diagnostic accuracy.

Sensitivity: The sensitivity of the CNN-LSTM algorithm is 0.9242, which is much greater than the CNN algorithm's 0.4749. This indicates that the CNN-LSTM technique is more efficient at detecting true positive instances, which is critical for accurately diagnosing lung conditions.

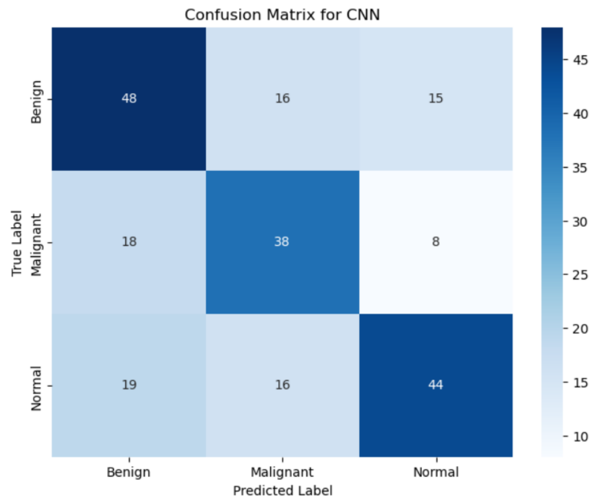

Fig. 3. Confusion matrix for the standalone CNN

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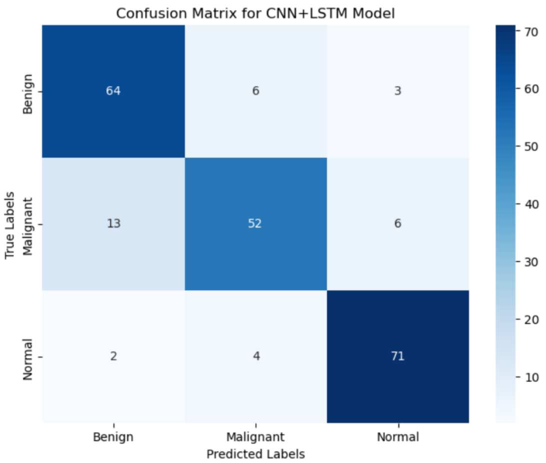

Fig. 4. Confusion matrix of the hybrid CNN+LSTM architecture.

The Figure 3 illustrates the confusion matrices for both models. The CNN model's matrix shows considerable misclassification, particularly between benign and normal cases. In contrast, Figure 4 illustrates the confusion matrix for the hybrid CNN-LSTM approach which demonstrates a higher rate of accurate classifications across all categories.

Figure 5 presents the accuracy curves over 20 epochs. The CNN-LSTM model consistently achieves higher accuracy, indicating its superior performance and ability to handle the dataset's complexity effectively.

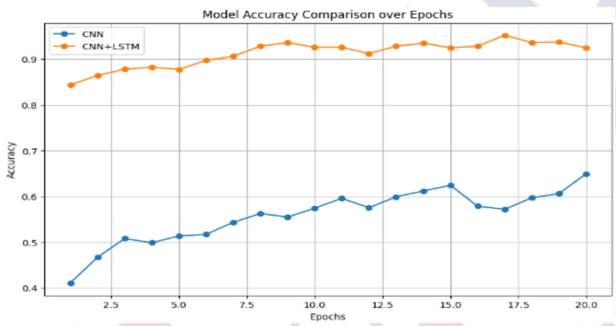

Fig. 5. Model accuracy comparison over epochs

The Figure 6 and 7 displays example images predicted by the hybrid CNN-LSTM model, showing its capability to classify images correctly as benign or malignant.

Fig. 6. Image predicted as benign by the hybrid model

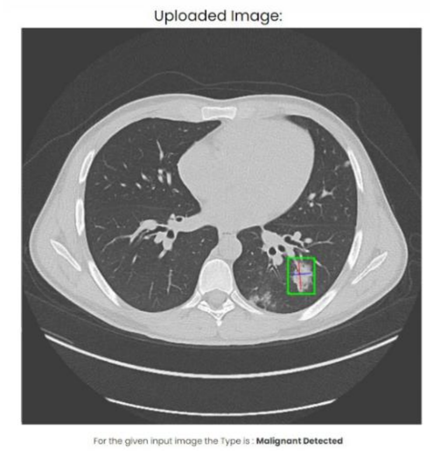

Fig. 7. Image predicted as malignant by the hybrid model

V. CONCLUSION

This study introduces a methodology for classifying lung CT images into malignant, benign, and normal categories using a robust dataset of 1,097 scans. The Hybrid CNN-LSTM model, after preprocessing, augmentation, and dataset splitting, achieves an accuracy of 92.46%, significantly outperforming the traditional CNN model's accuracy of 64.95%. This advancement is evident in the enhanced precision, recall, specificity, and sensitivity metrics. The results demonstrate the efficacy of merging CNN and LSTM architectures to improve classification accuracy. The CNN-LSTM model's ability to incorporate both temporal and spatial characteristics results in more reliable and accurate predictions, marking a significant advancement in lung nodule detection and classification. This approach offers promising implications for future medical image analysis research and applications.

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