A Novel CNN with Spatial and Channel Attention for Automated Chest X-Ray Diagnosis

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This study proposes a novel Convolutional Neural Network (CNN) approach with both spatial and channel attention mechanisms to improve automated chest X-ray image classification. The architecture integrates Squeeze-and-Excitation (SE) Blocks for channel attention and a spatial method to focus on informative regions of the sample, thereby enhancing both local and global feature extraction. The model processes input images of size 224×224×3 and comprises three convolutional blocks, each consisting of Conv2D, Batch Normalization, SE Blocks, Spatial Attention, MaxPooling, and Dropout layers. The dataset, sourced from Kaggle, contains 6,000 chest X-ray images categorized into three classes: Lung Opacity, Normal, and Viral Pneumonia. A standardized preprocessing pipeline was employed, including resizing, normalization (rescaling pixel values to [0, 1]), and real-time augmentation via TensorFlow's ImageDataGenerator. The model was trained for 10 epochs using a batch size of 32. It achieved a final test accuracy of 93.01%, with a peak validation accuracy of 88.57%, and an Area Under the Curve (AUC) score of 97.22%.

Povzetek: Za avtomatizirano analizo rentgenskih posnetkov prsnega koša so uporabili konvolucijsko omrežje, ki združuje kanalsko (SE) in prostorsko pozornost ter s tremi bloki učinkoviteje izlušči lokalne in globalne značilke.

1 Introduction

Lung diseases, including pneumonia, tuberculosis (TB), lung cancer, and chronic obstructive pulmonary disease (COPD) [23], remain among the leading causes of death worldwide. Early diagnosis and accurate detection of these conditions are crucial for improving patient outcomes and reducing the healthcare burden. Traditionally, radiologists have relied on chest X-rays to identify lung abnormalities. Still, this process is time-consuming, requires additional human resources, such as experts, and is prone to human error. As a result, there is acriticalneed for automated systems that can diagnose lung diseases more efficiently and accurately.

In recent years, the advent of deep learning (DL) and subset neural networks has revolutionized the field of medical image analysis. CNNs, a type of DL model, have demonstrated optimal performance in image classification, particularly in detecting lung problems from chest images. By training on numerous annotated medical images, deep learning models can automatically identify abnormalities in X-rays, providing a solution to the limitations of traditional methods. These models improve prediction accuracy and reduce the time required for analyzing multiple samples simultaneously, enabling faster decision-making with optimal clinical outcomes.

The DL approach used for detecting lung diseases from X-ray images was proposed by Al-qaness, M. A., et al. (2024) [1]. And the **c**hallenges associated with lung disease detection and how DL models can address these issues. Still, they can extract some complex features from the image that may be difficult for the human eye to detect. Additionally, it will examine the different architecture**s** and techniques employed in this domain, highlight the impact of large-scale annotated datasets, and discuss the practical applications of these models in clinical settings. But these simple CNN models will not capture sequential patterns from the samples.

Lung diseases such as pneumonia, tuberculosis (TB), lung cancer, and COPD are not only prevalent but also highly incurable if not detected in early stages. Early diagnosis is crucial for enhancing treatment outcomes and improving survival rates. For example, Pneumonia can cause severe respiratory pain if not diagnosed and treated with antibiotics. TB, on the other hand, is one of the foremost causes of death from an infectious disease, particularly in low-resource settings. In the case of lung cancer, the prediction is often poor if the disease is diagnosed at later stages, making early detection essential for survival. COPD is another common lung problem that can result in significant morbidity and mortality if not effectively managed. The global burden of lung diseases continues to rise, particularly in developing countries where medical resources are limited. The demand for effective and affordable diagnostic tools has grown in these regions.

Chest X-rays have been a vital diagnostic tool for lung diseases for decades. They provide a relatively inexpensive and accessible method for detecting abnormalities in the lungs. Radiologists assess X-ray images [8] to identify signs of disease, such as opacities and nodules, which can indicate various lung conditions. However, despite their importance, interpreting these images is challenging due to the complexity of the lung anatomy and the wide range of diseases that can occur in similar ways. These images are full of noise, which may bias the model.

The main challenges in lung disease detection are the complexity of the images, which includes model noise, and the interpretation, such as background color and the types of features extracted from image patches. Chest X-ray images often contain noise, artifacts, and variations in quality, making it challenging to capture complex features from raw data. In addition, the radiological manifestations of different lung diseases can be similar, such as nodules or **c**onsolidations that may appear in both lung cancer and pneumonia. Such overlapping symptoms increase the likelihood of misdiagnosis, especially when the images are reviewed by clinicians without the expertise or experience in interpreting lung X-rays.

Moreover, traditional diagnostic systems rely on radiologists' manual detection, which can be time-consuming and does not always provide optimal results. Radiologists, especially in busy healthcare settings, may not always have the time to thoroughly review all available X-ray images, resulting in delayed diagnoses. As the number of patients seeking diagnostic imaging services grows, the workload on radiologists also increases, further contributing to the potential for mistakes and missed diagnoses.

Researchers have turned to automated image analysis systems powered by deep learning or AI to overcome these challenges. Deep learning models are designed to learn and extract patterns from large datasets, making them ideal for analyzing medical images. These models can identify and classify diseases based on features that are complex for the human eye to perceive, such as delicate changes in texture, shape, depth, and size of structures in chest X-rays.

Deep learning, specifically through **CNNs** [11] and [12], has shown promise in medical image analysis. CNNs are a type of neural network designed to work with grid-like data such as images. These models automatically extract various features from input images, such as edges, textures, and patterns, without requiring manual feature engineering. This characteristic makes CNNs particularly effective for image classification tasks, including medical image analysis. In the context of lung disease detection, CNNs are trained on large datasets of labeled chest X-ray images that can classify the samples into healthy and diseased lungs. The model learns to identify visual patterns associated with different lung diseases, such as lung opacity, nodules, consolidation, and fibrosis, which can help classify diseases like pneumonia, TB, and lung cancer. Once a method is trained, these models can automatically analyze new X-ray images, providing accurate and rapid diagnoses. By using large-scale annotated samples, these models can achieve optimal performance. Although CNNs [13] and [19] neural network is used primarily for lung disease detection, recent advancements have introduced enhanced models that further improve performance and address existing limitations. These enhanced models incorporate techniques, such as transfer learning, data augmentation, and multi-task learning, to improve model accuracy and robustness.

Transfer learning is one of the most effective techniques in deep learning, particularly in scenarios where large labeled datasets are limited. By pre training a deep learning model [20] on a large number of images like ImageNet and these models can be fine-tuning on a smaller sample, specialized dataset like chest X-rays [21] will provide better results, transfer learning allows models to retain general knowledge while learning specific features relevant to lung disease detection.

Other recent innovations in deep learning for lung disease detection include the use of an attention approach, which enables patch-wise embedding and captures complex patterns from the image, and ensemble learning, where multiple models are combined to enhance predictive accuracy.

Contributions.

- Enhanced CNN with Spatial and Channel Attention Mechanisms for Improved Feature Extraction and Classification Performance.
- High-accuracy Chest X-ray Disease Classification Model Utilizing Attention Mechanisms to Improve Generalization and Robustness.

- Comprehensive Evaluation with Feature Importance Analysis Technique to Interpret Model Predictions and Enhance Explainability.

2 Related work

Many researchers have worked with machine and deep learning models, such as Shilpa, N., et al. (2024) [2], which have implemented various models, including ResNet50, MobileNetV2, AlexNet, and EfficientNetB0, to detect pneumonia in chest X-rays. Among all models, EfficientNetB0 performed the best. In this case, only one disease was detected using a pre-trained model. Sanida, T., et al (2024) [3] Implemented an optimized VGG model to detect multiple diseases, such as COVID-19, cancer, etc, in X-ray samples. I used 27,445 samples from all classes and applied augmentation methods to balance the dataset (Choudhry, I.). A et al. (2024) [4] implemented a deep learning model using cloud and fog methods to enhance security in the healthcare system. They employed a transfer learning method, such as RetinaNet, and fine-tuned EfficientNet models on chest X-ray samples.

KS, N., and Darapaneni, N. (2024) [5] implemented V-BreathNet model to detect the abnormality in X-ray, In this they first trained a customized CNN model on X-ray samples consist of 3 classes like phenomena, lung opacity and standard samples and got superior performance compared to VGG and Dense Net models. Paswan, J. D., et al (2024) in [6] pre-trained VGG, ResNet50, and DenseNet121 models on the COVID-19 dataset. This has only two classes, yes or no, and achieved an accuracy of 94% and 87% for training and testing, respectively.

Pan, C. T., et al. (2024) [7] proposed a two-stage data analysis method for the COVID-19 dataset, which consists of four classes: SARS, COVID-19, regular, and abnormal. First, all samples were converted to 224*224 dimensions after augmentation. I also trained various models, including VGG and GoogleNet, using 5-fold cross-validation; GoogleNet performed particularly well.

Mahamud, E., et al. (2024) [9] proposed an enhanced DenseNet201 model with a transformer approach using X-ray data. With Explainable AI, trained on 10000 samples over four classes, and got an accuracy of 1.0. Kotei, E., and Thirunavukarasu, R. (2024) [10] developed a method for detecting Tuberculosis disease using pre-trained CNN models on X-ray images. First, all samples were converted to a 256-gray scale, and the CNN model was trained, achieving an accuracy of 99%. Hansun, S., et al. (2023) [14] utilized the QUADAS-2 dataset, comprising 309 samples, to train ML and DL models, achieving an accuracy of 0.93 with ML models in detecting TB. Malik, H., et al. (2023) [15] implemented a pre-trained CNN model to detect various diseases, such as TB and pneumonia, from X-ray samples, achieving an accuracy of 0.99, which is better than that of overall transfer models.

Chen, Y., etal. (2023) [16] optimized EfficientNet-b5 and CoAtNet-0-rw using different loss functions, including novel and weighted binary loss functions. This model is trained on the ChestX-ray14 dataset, which comprises 14 classes, and achieves an accuracy of 0.842.

Bharati, S., et al (2020) implemented a hybrid DL model by combining CNN and VGG on lung disease detection and trained various combinations; in this, they got an accuracy of 0.73% with the best model. Ganeshkumar, M., et al. (2023) [18] proposed a two-stage learning ensemble method for classifying regular pneumonia and COVID-19 Pneumonia. The total number of samples is 600. This ensemble model achieved an accuracy of 0.89.

Mustafa, Z., and Nsour, H. (2023) [22] proposed a YOLO pre-trained model for detecting respiratory infections and TB using X-ray images. Reamaroon, N., et al. (2021) [24] extracted gray-level co-occurrence matrix-based features, trained a machine learning model using k-fold cross-validation and the Adam optimizer, and achieved an accuracy of 0.83. Chen, K. C., et al. (2020) [25] focused on pulmonary diseases in children, utilizing X-ray images to train a YOLO model, achieving an accuracy of 0.92.

[26] Benchabane&Charif (2025). In this work, we integrate deep learning with advanced image enhancement to enhance the detection of COVID-19 through chest X-rays. The proposed approach demonstrates superior diagnostic performance, underscoring the contribution of pre-processing to enhancing model accuracy. [27] Oraibi&Albasri (2023) The authors present a robust end-to-end CNN architecture that addresses the issue of data imbalance in COVID-19 detection. The model's accuracy is high on X-ray datasets, and focusing on balanced training and architectural optimization strategies is onekey reason.

3 Methodology

We designed a custom CNN architecture that incorporates spatial and channel attention mechanisms to enhance the extraction of complex features, such as local and global variations, as well as background and foreground, from images. The model processes 224×224×3 RGB embedded vectors, which are normalized between 0 and 1 to improve training stability and remove the domination of background vectors.

The CNN consists of three convolutional blocks, each incorporating Conv2D, Batch Normalization, Squeeze-and-Excitation (SE) Blocks, Spatial Attention Layers, MaxPooling, and Dropout layers. The SE Block applies channel attention by adaptively recalibrating feature responses, enhancing relevant features while suppressing redundant ones. Meanwhile, the Spatial Attention Layer emphasizes critical spatial regions by computing attention maps based on average and max-pooled feature maps.

Each convolutional block consists of a Conv2D layer with a 3×3 kernel, ReLU activation, and 'same' padding, extracting hierarchical spatial features from each 3*224*224 sample. A Batch Normalization method is applied to normalize the embedded vectors within the range of 0 to 1, which is then passed to the convolutional layer, where it normalizes the features, thereby reducing internal adjustments.

The SE Block, responsible for channel attention, consists of three key steps:

1. Global Average Pooling will find the average value of each global feature map.
2. Bottleneck dense layers, which consist of two fully connected layers, adjust the channel dimensions. The first dense layer (with ReLU activation) reduces the number of filters by a factor of 16, and the second dense layer (with a sigmoid activation) restores the original filter count.
3. Reshaping and Multiplication – The recalibrated weights are applied to the input feature maps, improving feature selection.

The final classification layers include a flatten layer that converts a multidimensional matrix into 1D data and sends 1D data to a dense layer with 256 units. The thick layer, with ReLU activation, provides nonlinear values for the given input, allowing it to learn complex foreground features. A Dropout method with a 50% rate is applied to prevent overfitting, where 50% of neurons are dropped from the training process after each epoch.

4 Data set

The dataset used for lung disease classification was obtained from Kaggle. It comprises chest X-ray samples labeled into three classes, totaling6000, as shown in Figure 1. The data set consists of a mixture of dimensions, depths, and sizes, so a standardized preprocessing pipeline was applied to ensure consistency in input dimensions and facilitate practical model training.

Initially, we employed the ImageDataGenerator class in TensorFlow to handle image augmentation and rescaling. The training dataset was augmented using ImageDataGenerator with a normalization factor of 1/255to scale pixel values between 0 and 1. A validation split of 20% was applied to ensure a fair model evaluation. Separate ImageDataGenerator instances were also used for validation and test datasets, with rescaling applied uniformly across all datasets. The images were loaded into TensorFlow data generators using the flow from data frame method, which sourced image file paths and corresponding labels from structured data frames.

Additionally, we implemented a preprocessing pipeline using TensorFlow's Sequential API to standardize image dimensions. This involved a Resizing layer to reshape images to a fixed size of (224,224), ensuring uniformity across the dataset, followed by a Rescaling layer to normalize pixel values. Figure 2 illustrates the number of samples for each class before augmentation.

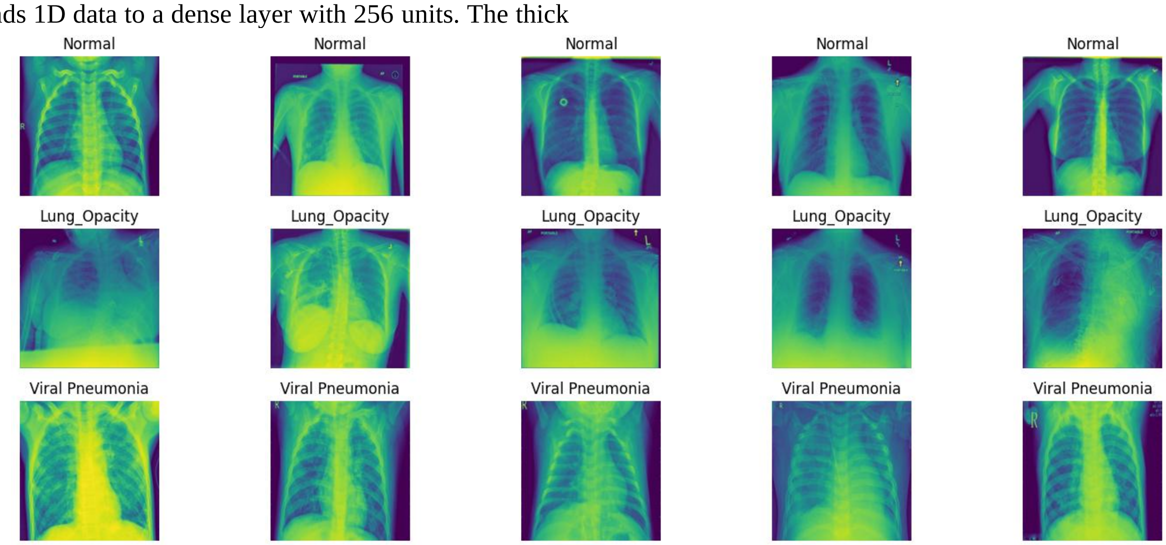

Figure 1: Shows X-ray images of the disease and normal.

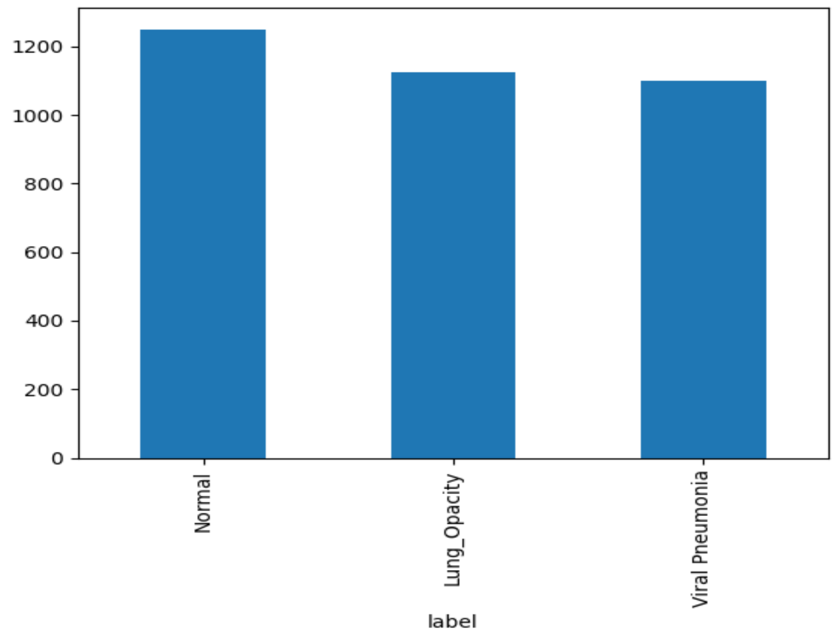

Figure 2: Class-wise number of samples before augmentation

5 Result analysis

The proposed CNN model, with spatial and channel attention mechanisms, was trained for 10 epochs to classify chest X-ray images into three categories: Lung Opacity, Normal, and Viral Pneumonia. The model was trained using a batch size of 32, with accuracy and loss metrics recorded for both the training and validation datasets at each epoch, as shown in Figure 3.

During the early training epochs, the model showed consistent improvement in classification performance. By Epoch 4, the accuracy reached 87.17%, with a slightly lower validation of 78.57%, indicating that the model was still learning to generalize to unseen patterns. This trend continued into Epoch 6, where training accuracy rose to 90.08% and validation accuracy improved to 82.86%, demonstrating better generalization. Concurrently, the training loss decreased from 0.3160 to 0.2570, and the validation loss dropped from 0.4803 to 0.3691.

A notable improvement occurred in Epoch 7, with training accuracy at 89.98% and validation accuracy peaking at 88.57%. The corresponding validation loss further reduced to 0.2566, suggesting increased model stability and effective feature learning. However, by Epoch 9, validation loss spiked to 0.5656 despite a high training accuracy of 92.70%, indicating potential overfitting. This was confirmed in Epoch 10, where validation loss sharply increased to 1.0427 and validation accuracy stagnated at 82.86%, suggesting that the model had begun to memorize the training data rather than generalize effectively.

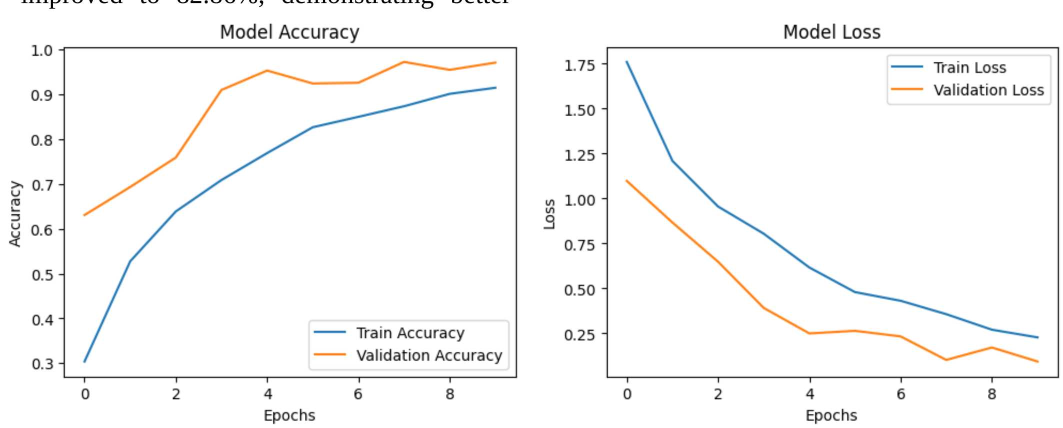

Figure 3: Learning curves of the proposed model

The proposed model achieved an overall accuracy of 93.93%**,** as shown in Figure 4, demonstrating its effectiveness in classifying into three classes: lung opacacity, normal opacacity, and viral pneumonia. The model exhibited strong predictive performance across all classes, with high correctness in identifying both positive and negative cases. Specifically, for Lung Opacity, the model maintained perfect results in correct classifications and misclassifications, ensuring high reliability. Similarly, the classification performance for Normal cases remained consistent, with minimal errors. The highest performance was observed in detecting Viral Pneumonia, where the model exhibited superior capability in distinguishing these cases from the other categories, reflecting its ability to capture distinctive patterns in the dataset.

The overall effectiveness of the model was further reinforced by its ability to maintain a strong balance across different performance metrics, reducing both false positives and false negatives. The comprehensive evaluation metrics indicate that the model extracted complex spatial and temporal features and provides robust decision-making. Additionally, the model provided a substantial area under the curve (AUC) score of 97.22%, highlighting its ability to differentiate between categories with high confidence, as illustrated in Figures 5 and 6. The combination of spatial and channel attention mechanisms contributed significantly to feature enhancement, improving classification accuracy and better generalization across chest X-ray samples.

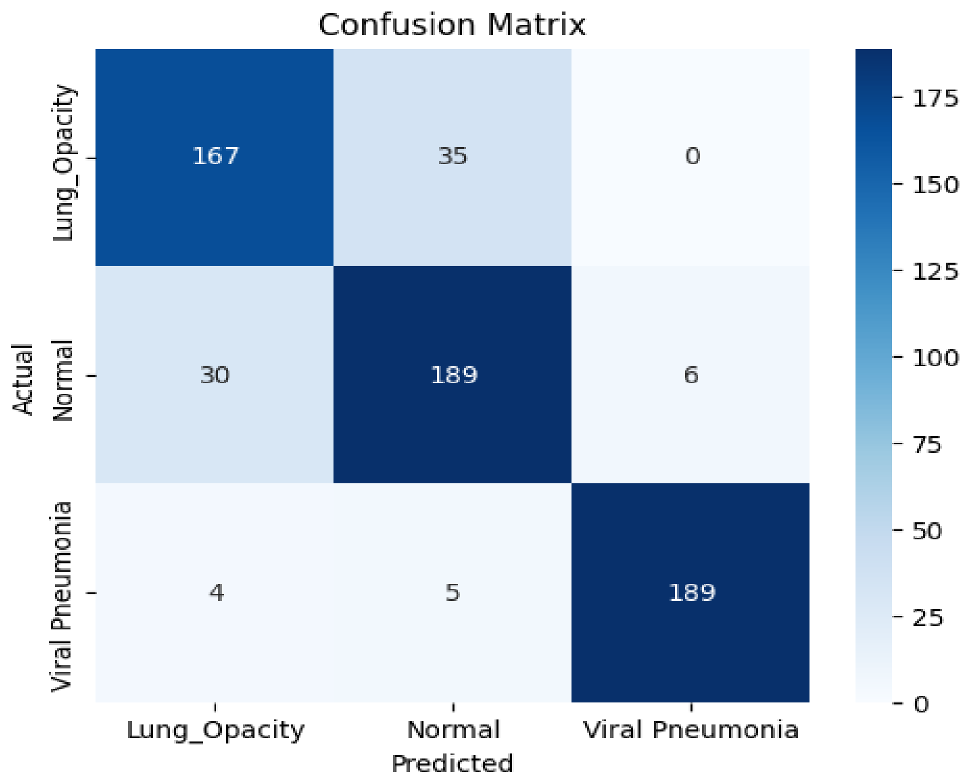

Figure 4: Confusion matrix of the proposed hybrid model

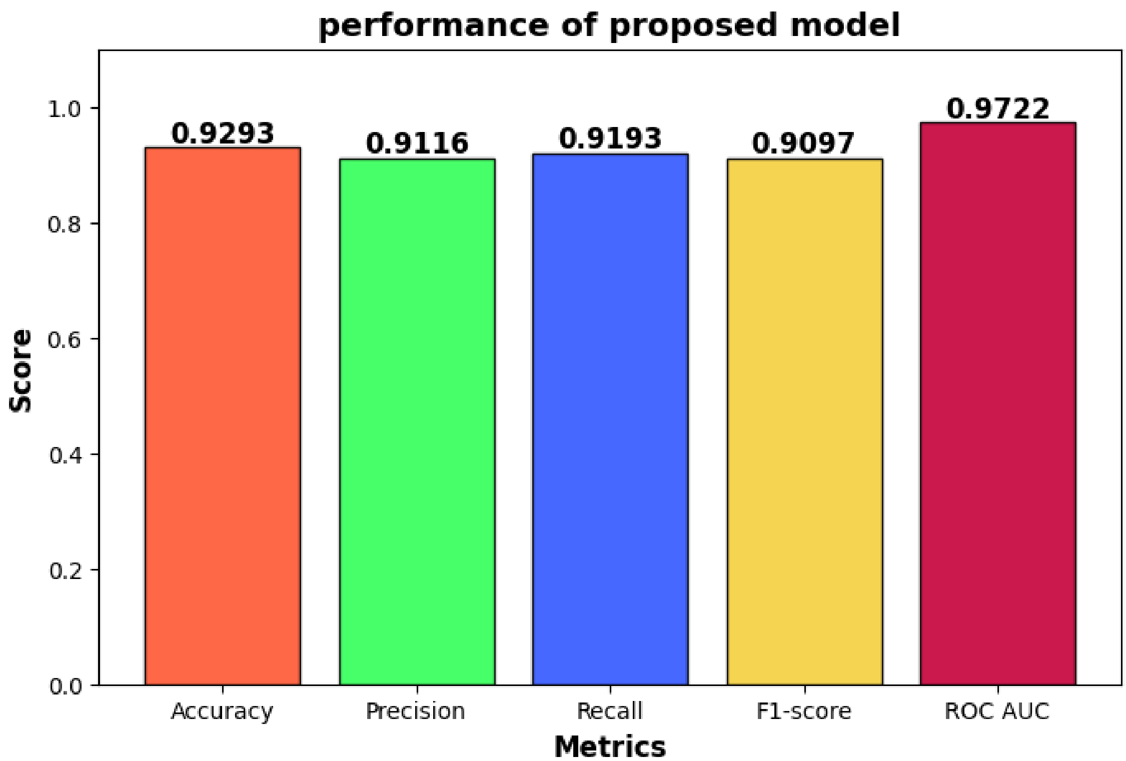

Figure 5: Proposed model performance on various metrics

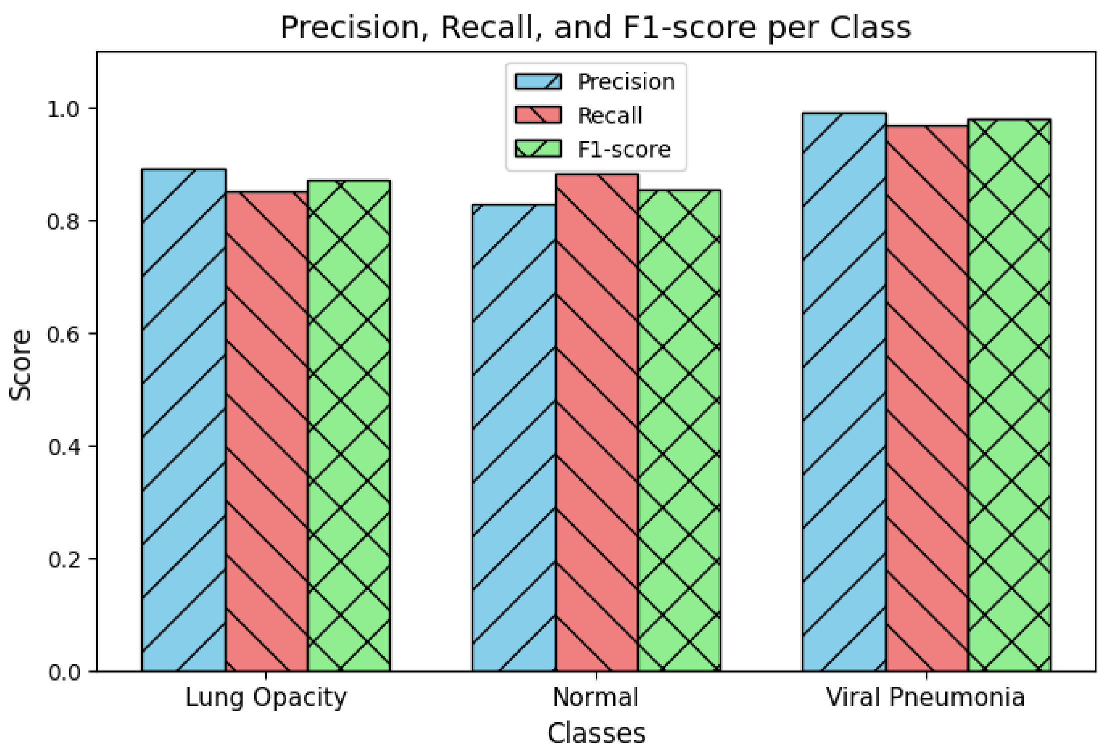

Figure 6: Class-wise performance of proposed hybrid model

Figures 5 and 6 show that the ROC and PR curves from Figure 7 illustrate the model's performance over three classes—Lung Opacity, Normal, and Viral Pneumonia. The ROC curve accuracy shows that the model achieves a high AUC for all courses, 0.97, with Viral Pneumonia approaching an ideal classification boundary. The PR curve demonstrates the presentation of the model on three classes. The slight reduction in precision at higher recall values, particularly for the Normal and Lung Opacity classes, suggests that the model provides strong predictive capability. Figure 8 represents the importance of features using permutation-based analysis, highlighting the role of different features in the model's executive process. The color gradient visually distinguishes features based on their relative importance, where taller bars indicate higher significance. The black error bars depict variability in importance scores across multiple iterations, ensuring robustness in feature selection.

From table 1 it is observed thatPaswan et al. [6] with pre-trained method like VGG, ResNet50, and DenseNet121 on a COVID-19 dataset and reported a training accuracy of 94% and a testing accuracy of 87%, targeting binary classification (COVID-19 vs. non-COVID). Hansun et al. [14] used both machine learning (ML) and deep learning (DL) models on the QUADAS-2 dataset comprising 309 samples to detect tuberculosis (TB), achieving an overall accuracy of 93%. Chen et al. [16] fine-tuned EfficientNet-B5 and CoAtNet-0 on the ChestX-ray14 dataset, which contains 14 classes of chest diseases, and achieved a multi-class classification accuracy of 84.2%. Similarly, VDSNet [17] was trained on 5,606 samples from the same dataset and achieved 73% accuracy across 14 disease classes, demonstrating the complexity of multi-class classification with high disease variability.

Ganeshkumar et al. [18] proposed an ensemble learning approach on a smaller dataset of 600 chest X-rays to distinguish between regular and COVID-19 pneumonia, reaching an accuracy of 89%. In another approach, Mustafa and Nsour [22] employed a pre-trained YOLO model to detect TB and respiratory infections, although specific performance metrics were not reported. Reamaroon et al. [24] used gray-level co-occurrence matrix (GLCM) features with ML classifiers to detect respiratory infections, achieving 83% accuracy. Chen et al. [25] applied YOLO to pediatric pulmonary X-ray images, attaining a classification accuracy of 92% in detecting childhood pulmonary diseases.

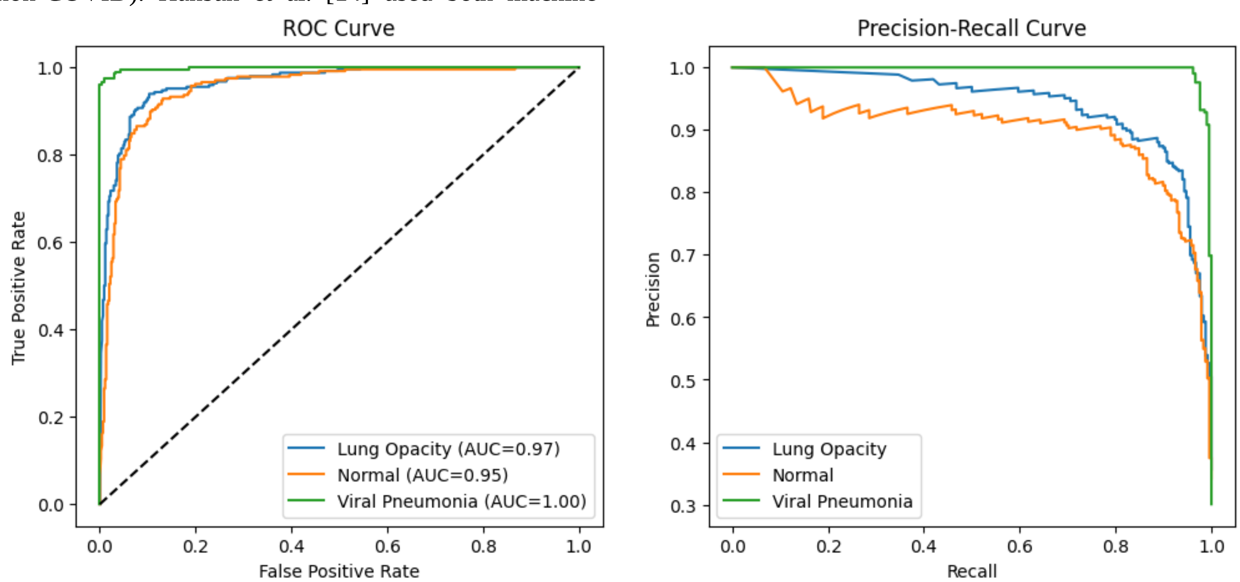

Figure 7: ROC, precision-recall curves of the proposed hybrid model

Table 1: Comparison of proposed hybrid model with prescribed models

Ref	Model /	Dataset / Sample Size	Disease(s) Detected	Classes	Accuracy / Performance
[6]	VGG, ResNet50, DenseNet121	COVID-19 Dataset	COVID-19	2	Train: 94%, Test: 87%
[14]	ML and DL Models	QUADAS-2 / 309 samples	Tuberculosis	2	93%

[16]	EfficientNet-B5, CoAtNet-0	ChestX-ray14 (14-class)	14 Chest Diseases	14	84.20%
[17]	VDSNet	ChestX-ray14, 5606 samples	14 disease	14	73%
[18]	Ensemble Learning	600 X-rays	Pneumonia (Regular vs. COVID-19)	2	89%
[22]	YOLO (Pre-trained)	Chest X-rays	TB, Respiratory Infections	Multi	N.A.
[24]	ML + GLCM Features	X-rays / N.A.	Respiratory Infections	2	83%
[25]	YOLO	Pediatric Pulmonary X-rays	Pulmonary Disease in Children	2	92%
#	Proposed model	Chest X-rays, 3475 samples	Pneumonia, normal,lung opacacity	3	93.01%

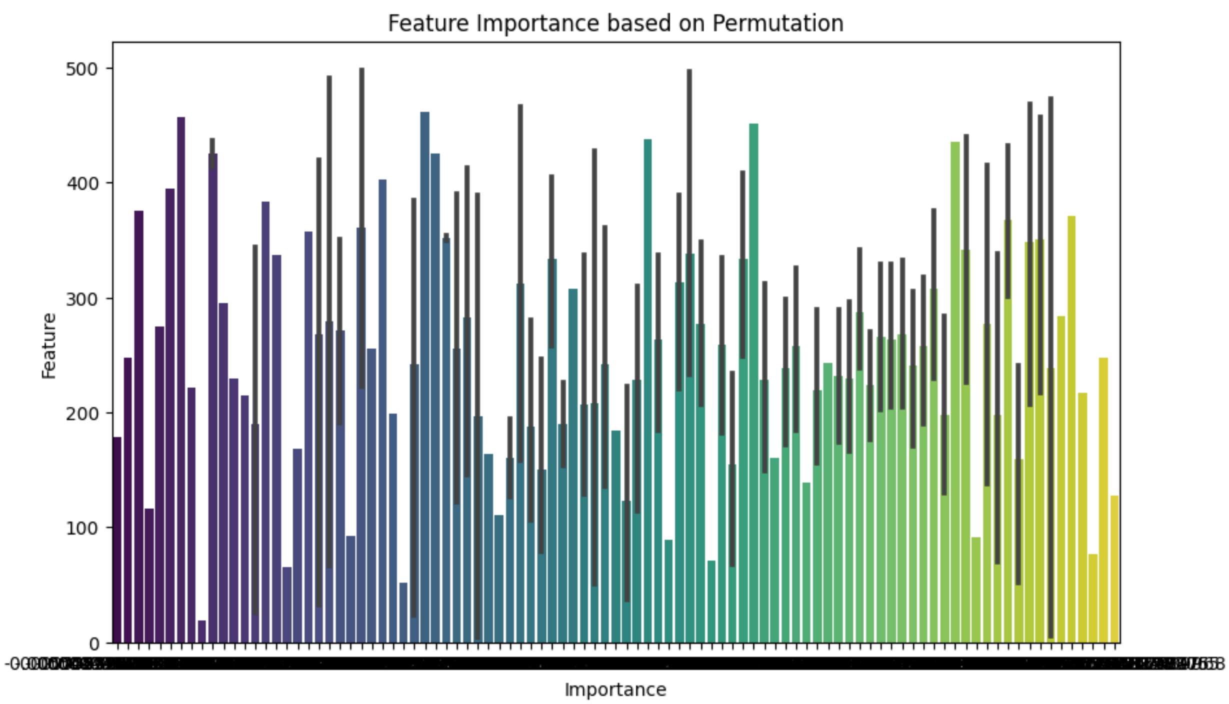

Figure 8: Features the importance plot after training

6 Conclusion

This study proposed a novel CNN architecture enhanced with spatial and channel attention mechanisms for automated chest X-ray classification, achieving high classification accuracy and strong generalization capabilities. Integrating SE Blocks and Spatial Attention Layers improved feature representation, enabling the model to distinguish between Lung Opacity, Normal, and Viral Pneumonia with an overall accuracy of 93.01%. Performance analysis using ROC and Precision-Recall curves confirmed the model's ability to maintain high precision and recall across all classes. However, training dynamics indicated overfitting in later epochs, suggesting the need for further optimization through regularization techniques and extended training datasets. Future work will enhance model robustness by incorporating advanced augmentation techniques and exploring hybrid deep learning architectures.

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