Attention-Based Deep Learning Model for Robust Pneumonia Classification and Categorization using Image Processing

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Abstract. A serious respiratory illness that causes inflammation in the lungs, pneumonia poses serious health concerns. Recent advancements in deep learning have revolutionized pneumonia detection by enabling automated, accurate, and efficient diagnosis. This project makes use of the ResNet152V2 pre-trained model with Convolutional Block Attention Module (CBAM) to further feature enhancement and classifies using neural network. The novelty of this paper highlights categorization of pneumonia into stages into Mild, Moderate and Severe pneumonia based of lung opacity values. The benchmark Kermany dataset from Kaggle is utilized and the model achieved 93.10% accuracy. To improve accessibility, a web application has developed that allows easy and efficient use of the model for real-time pneumonia detection. By integrating AI-driven diagnostics with a user-friendly interface, this project enhances early detection, reduces diagnostic errors, and contributes to improved health- care accessibility in resource-limited settings. This approach not only ensures high diagnostic precision but also facilitates timely medical intervention. The integration of CBAM with ResNet152V2 enhances feature discrimination, while stage-wise severity classification supports tailored treatment strategies. The user-centric web interface bridges technological advancements with clinical usability, promoting equitable healthcare delivery in underserved areas.

Keywords: Transfer learning, Attention Mechanism, ResNetv2152, CBAM Attention, Gaussian blur, Contour extraction, Lung opacity

1 Introduction

Pneumonia is a potentially fatal lung disease that is marked by air sac inflammation and is typically bacterial, viral, or fungal infection. It is a dangerous threat to the public health, especially to children, elderly patients and patients with compromised immune systems. The timely and correct diagnosis is a pre- condition to improved treatment and improved patient outcomes. Interpretation of chest X-rays by radiologists is the cornerstone of traditional diagnosis methods, which are time-consuming and prone to human error.

Medical imaging has undergone a revolution of recent developments in artificial intelligence, especially deep learning. By examining chest X-ray pictures, deep learning algorithms have demonstrated an impressive level of accuracy in identifying pneumonia. CNNs are one of these that have been used extensively because of its capacity to recognize complex features

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and characteristics in images related to healthcare domain. However, for dependable real-world applications, more accuracy and robustness advancements are necessary.

Pneumonic X-rays can be distinguished from healthy ones by their infiltrates, which are white patches in the lungs.[3] explains that Attention mechanisms have significantly improved image classification and segmentation by dynamically focusing on salient regions, enhancing feature representation, and reducing irrelevant information. In classification, they refine feature extraction in CNNs and transformers, improving accuracy. [5] This paper explains the significance of ensemble model that enhances the accuracy by combining the two individual pre-trained models in image classification.

This research proposes a novel approach to pneumonia detection using the ResNet152V2 pre-trained model integrated with a CBAM attention. The combination of ResNet152V2 and CBAM enhances feature extraction by concentrating on crucial regions within the chest X-rays. This refined feature representation, processed by a deep neural network (DNN), significantly improves the classification accuracy. Then Gaussian blur is applied and contours are extracted, then opacity value is calculated. Based on this opacity value the pneumonia is categorized.

The Kaggle Kermany dataset, which includes chest X-ray pictures categorized as either pneumonia or normal, was used to test the suggested model. The model was successful in differentiating between pneumonia and normal patients, as evidenced by its 93.10% accuracy. Additionally, a user-friendly web application has been developed to facilitate real-time pneumonia detection, enhancing accessibility for healthcare providers in resource-limited settings.

This research makes a significant contribution to pneumonia detection. The major contributions and the novelty of this paper highlights:

- It demonstrates remarkable performance in differentiating between pneumonia and normal conditions by utilizing CBAM Attention with 93.10% accuracy.
- Categorization of Pneumonia by utilizing image processing techniques into mild, moderate and severe classes.
- Developed a web-based application, enabling users to conveniently and effectively perform real-time pneumonia detection using the proposed model.

The organization of this paper is as follows: A judicious critique of previous work is described in Section 2. The methodology that we suggest, featuring feature extraction, preprocessing of data, and model construction are described in Section 3. Experimentation Results are described in Section 4, together with the evaluation of a model on a range of performance measures. Principal findings and future enhancements for subsequent research are lastly presented in Section 5 conclusion.

2 Related works

[1] employs the EfficientNetV2L model to suggest a new pneumonia detection model and contrast it with CNN, InceptionResNetV2, Xception, VGG16, and ResNet50, five additional deep learning models. EfficientNetV2L performed best with a record accuracy of 94.02%. k-

fold cross-validation and data augmentation and preprocessing methods were employed by the study to maintain robustness and enhanced model performance.

[2] introduces a new technique for detecting COVID-19 pneumonia that combines channel and spatial attention mechanisms with a multi-scale convolutional neural network. The model improves feature ex- traction for better lesion diagnosis and is based on the Res2Net50 architecture. The suggested approach outperformed conventional models such as ResNet18, ResNet50, and DenseNet201 with an accuracy of 93.59% when tested on the COVQU dataset, which comprises 18,479 chest X-ray images.

[3] highlights that attention mechanisms have greatly enhanced image classification and segmentation by dynamically concentrating on important regions, thereby improving feature representation and minimizing irrelevant information. In classification tasks, they enhance feature extraction in CNNs and transformers, leading to improved accuracy.

[4] offers a study uses CNNs to diagnose pneumonia. The study evaluates three models: a specially built CNN model, VGG16, and VGG19. To extract and categorize features, VGG16 and VGG19 underwent transfer learning. The best results were obtained by the custom CNN, which outperformed the transfer learning models with ac- curacy of 93%. The study demonstrates how well CNNs recognize chest X-ray images to identify pneumonia.

[5] explains the effectives of hybrid models in image classification. This study used ResNet50 and VGG19 as feature extraction and used DNN for classification of Diabetic retinopathy into stages. It achieved 83.33% accuracy which outperforms the individual transfer learning models. It highlights use of hybrid models of CNNs for accurate classification.

[6] focuses on classifying cases into viral, bacterial, and normal using Inception V3 and MobileNet V2 for feature extraction. Trained on a curated dataset of 9208 images, MobileNet V2 achieved 95.99% accuracy, outperforming Inception V3’s 84.81%, highlighting its effectiveness for practical medical applications in pneumonia detection.

[7] offers a technique through chest X-ray images for pneumonia detection. Through the application of a weighted average ensemble strategy, researchers combined three convolutional neural net- works namely DenseNet, ResNet, and GoogLeNet. The system scored high ac- curacy of 98.81% and 86.85%, as well as sensitivity of 98.80% and 87.02%, when tested based on two datasets.
[8] This study introduces a deep learning approach using a re-attention mechanism with Vision Transformer (ViT) for pneumonia detection. By effectively focusing on key regions in chest X-rays and capturing both local and global features, the model achieved 86.69% validation accuracy on the Kaggle dataset, outperforming conventional and previous re-attention methods.

[9] recommends using an Ensemble Learning (EL) approach using transfer learning of DenseNet169, MobileNetV2, and Vision Transformer (VIT). This EL approach uses transfer learning and fine-tuning to combine data from many models for better classification. The ensemble approach fared better with 93.91% accuracy.

[10] study uses CNN and Transfer Learning to automate pneumonia diagnosis from pediatric chest X-rays. While CNN achieved 89% accuracy, Transfer Learning performed better at 93%. An ensemble of both approaches delivered the best precision and recall, with 92% accuracy, highlighting the potential of AI tools for early and accurate pneumonia detection.

[11] An ensemble of ResNet-34 and EfficientNet-B4 U-Net models improves pneumonia diagnosis, addressing class imbalance with Gaussian smoothing and augmentation. The model achieved 90% accuracy and high precision-recall, proving the value of combining complementary features.

[12] investigates deep learning for pneumonia identification utilizing kaggle imageset of 5,863 images that have been divided between normal and pneumonia- infected images. Several architectures are used, such as CNN, MobileNet, and ResNet; CNN achieves 91% accuracy, while an LSTM model achieves 90.2% accuracy.

[13] describes the process of creating the automatic detection of pneumonia. In addition to showing that CNN models, like DenseNet121 and Xception, exhibit high accuracy (above 86%) and sensitivity (above 91%), it also high- lights the limitations of human radiologists in accurately detecting pneumonia. The study emphasizes the importance of larger datasets to improve model performance and reduce overestimation of accuracy.

[14] suggests a modified CNN architecture for the identification of pneumonia. The performance of a bespoke 35-layer CNN, VGG16, and VGG19 is compared in the study. The updated CNN obtained the maximum accuracy of 96.3% using a Kaggle dataset. The model outperformed VGG16 (94.1% accuracy) and VGG19 (95.7% accuracy) in classification.

[15] shows how to use CNNs for images in order to detect pneumonia. A novel CNN model was developed from the ground up and trained using augmented data to improve accuracy and prevent overfitting. After 25 training epochs, it demonstrated strong performance with accuracy of 92.47%.

[16] study applies deep learning for pneumonia detection, emphasizing preprocessing steps like lung segmentation, histogram equalization, and image resizing. VGG16 is used as the baseline model due to its superior accuracy, with data augmentation and outlier removal further boosting performance.

[17] A Sparse-Attention Based DCNN (SA-DCNN) enhances pneumonia detection by focusing on condition-specific features. Using transfer learning with models like Xception, InceptionV3, VGG16, and ResNet50, the sparse attention module boosts diagnostic accuracy and feature quality.

[18] DeepConvDilatedNet, based on Faster R-CNN, enhances pneumonia diagnosis by integrating a Feature Pyramid Network (FPN) and a dilated bottleneck residual network for improved feature extraction. It also optimizes anchor box generation using K-Means++ and refines bounding box selection with Soft-NMS.

[19] study explains using ResNet101 with CBAM attention improved spatial and channel feature extraction from chest X-rays, achieving 82.85% accuracy. The CBAM-enhanced

model outperformed standard ResNet101 by addressing sample imbalance and boosting diagnostic accuracy.

3 Methodology

To examine pneumonia detection, a comprehensive strategy for data exploration, preprocessing, and feature extraction is required to improve classification models. Chest X-ray image data must be carefully processed to extract meaningful features that enhance the model's performance and robustness. Methods of preprocessing like data augmentation and normalization are applied to improve generalization, while a pre-trained model like ResNet152V2 is utilized for feature extraction. By leveraging the advantages of ResNet152V2 and incorporating the CBAM attention, the classification model is enhanced with refined feature representation. This integration, along with a deep neural network (DNN), improves the model's diagnostic accuracy by capturing essential spatial and contextual information from X-ray chest images.

3.1 Dataset Collection

There are 5,856 photos in the dataset used for this pneumonia detection, which is divided into train, test, and validation sets. This image dataset contains images related to Pneumonia class and Normal class. Kaggle imageset link: https://www.kaggle.com/datasets/paultimothymooney/chest-xray-pneumonia. Table 1 gives the image categories and its count.

Table 1. Images Categories and its count.

	Total images
Pneumonia	4273
Normal	1583
Total	5856

3.2 Preprocessing

The preprocessing of X-ray images was performed utilizing Keras' ImageDataGenerator. All images were rescaled to the [0,1] range by normalizing pixel values with a factor of 1/255. Data augmentation techniques, including random shear transformations (20%), zoom variations (20%), and horizontal flipping, were ap- plied to the training images to enhance model generalization. The images were resized to 300×300 pixels before feeding them into the network. The validation and test datasets were only rescaled without augmentation to maintain consistency in evaluation. This preprocessing strategy ensured robust feature extraction and improved classification performance by reducing overfitting to training data.

3.3 Feature Extraction using ResNet152v2

A modified form of the residual network architecture is known as ResNet152V2. The layers of ResNet152V2 consist of one average pooling layer, one max pooling layer, and 151 convolutional layers. In pneumonia detection, after receiving an input chest X-ray image, the top Dense (fully connected) layers are removed for feature extraction, utilizing only convolutional layers to capture important characteristics from lung images. These extracted features help in distinguishing Pneumonia affected lungs from normal ones. ResNet152V2 employs the residual learning concept to solve the vanishing gradient issue in deep neural networks, enabling the efficient training of very deep architectures. The initial convolutional layers learn fundamental image features like edges and textures. As the network deepens, more complex and critical patterns related to pneumonia are identified in the X-ray images. The training set of chest X-ray images is fed into this pre-trained ResNet152V2 model to extract significant feature representations. Fig 1 gives the architecture of RestNet 52V2.

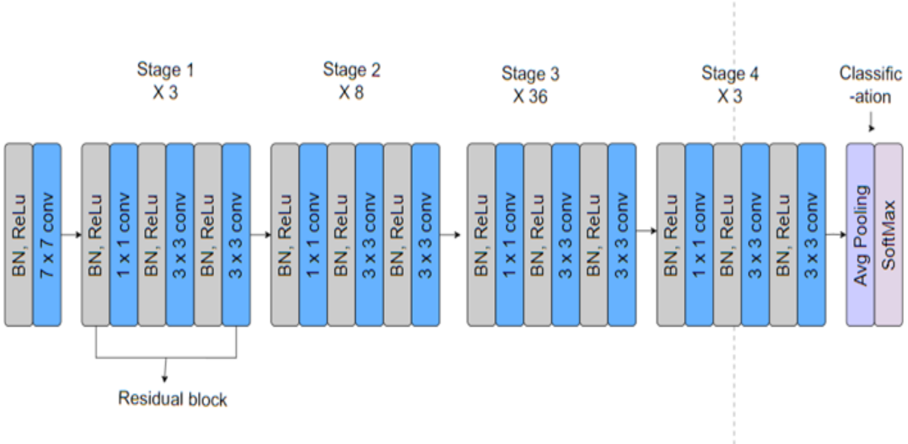

Fig. 1. Architecture of ResNet152V2.

Mathematical Formulation

Residual Block: The fundamental ResNet building block utilizes skip connections to learn residual functions. Assuming the block's input is xxx and the desired mapping to learn is F(x)F(x)F(x), the block's output is given by:

$$Output \;=\; F\,(x) \;+\; x \tag{1}$$

Residual Function: A ResNet block's residual function, F(x), is typically rep- resented as the combination of multiple layers, including activation functions, convolutional layers, and batch normalization:

$$F\,(x) \;=\; Conv(x) \;+\; BatchNorm\,(ReLU\,(Conv(x))) \tag{2}$$

3.3 Feature Extraction using CBAM (Convolutional Block Attention Mechanism)

The CBAM attention is an advanced feature sharpening mechanism that strengthens convolutional networks through spatial and channel-wise attention, allowing the model to focus on important areas and informative features. It is composed of two attention modules: the Channel Attention Module, which gives importance to feature maps through different channels, and the Spatial Attention Module, which sharpens feature maps with regard to spatial information. In the detection of pneumonia, CBAM enhances feature extraction through focusing on important lung abnormalities such as infiltrates, allowing for better sensitivity to fine patterns in chest X-ray images, hence enhancing classification accuracy.

Channel Attention Module (CAM) – Determines what is important by weighting feature maps across different channels. Spatial Attention Module (SAM) – Determines where is important by refining feature maps based on spatial information. Fig 2 gives the architecture of CBAM.

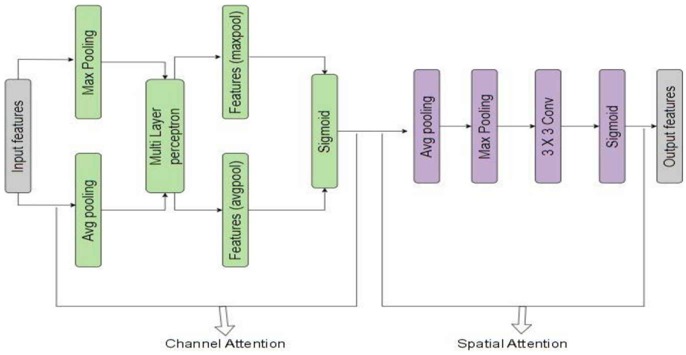

Fig. 2. Architecture of CBAM.

3.5 Deep Neural Network for Classification

Deep neural networks (DNNs) are highly efficient for classification tasks, leveraging multiple layers to extract meaningful patterns from data. In this pneumonia detection model, the feature maps are obtained from ResNet152V2 with CBAM to refine important spatial and channel-wise features. These feature maps are then passed to a neural classifier with layers structured as 1024 → 512 → 256→ 128 → 64 → 32, where each layer uses the ReLU activation function to ex- tract and refine features. The final classification is performed by a sigmoid layer, assigning probabilities to pneumonia and normal classes. The model is trained using backpropagation, adjusting weights to minimize classification errors. After training, the model predicts class labels for unseen images, ensuring robust performance in detecting pneumonia with high accuracy and reliability.

Mathematical formulae: A Dense layer’s output is provided by

$$pre - activation(x) = (w * x + b) \tag{3}$$

ReLU function for all dense layer:

$$ReLU\ (x) = max(0, x) \tag{4}$$

Sigmoid function for classification layer:

$$Sigmoid(x) = 1 / (1 + e\hat{}(-x)) \tag{5}$$

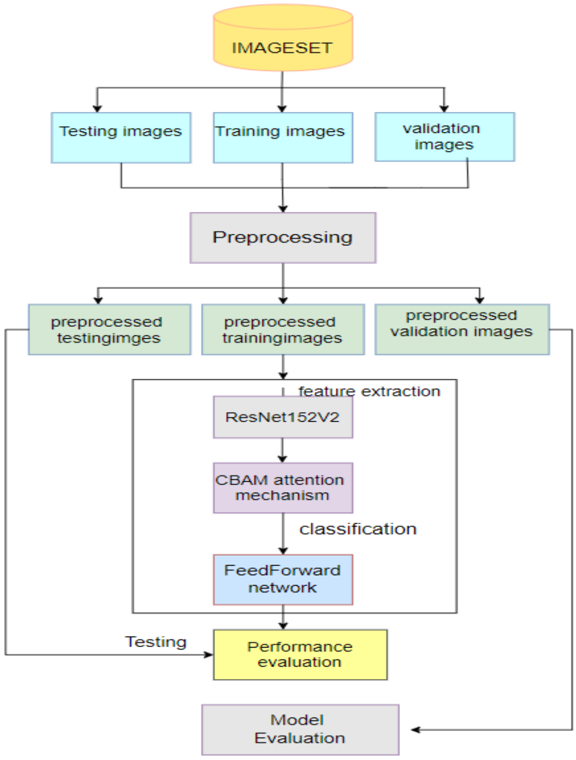

Fig. 3. Generic Architecture of proposed model.

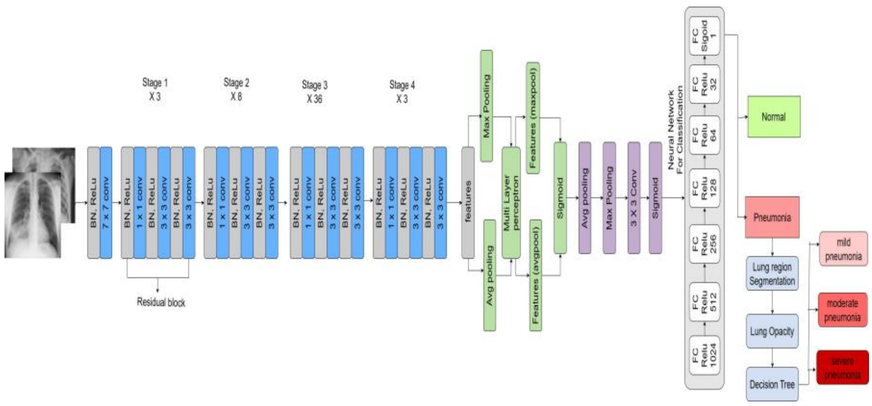

Fig. 4. Proposed Architecture.

Fig 3 shows the generic architecture of proposal model and fig 4 shows the proposed architecture.

Algorithm 1: Pneumonia Classification and Severity Prediction using ResNet152V2 with CBAM Attention

Step 1: Feature Extraction using ResNet152V2
Load pre-trained ResNet152V2 model
Remove fully connected layers
Extract feature maps from the last convolutional layer
Step 2: Apply CBAM Attention Mechanism
foreach *extracted feature map F* **do**
    Compute channel attention: $F_{CA} \leftarrow CBAM\_Channel\_Attention(F)$
    Compute spatial attention: $F_{SA} \leftarrow CBAM\_Attention\ (FCA)$
    Obtain refined features: $F_{CBAM} \leftarrow F_{SA}$
end
Step 3: Classification using Neural Network
Flatten CBAM-enhanced feature maps
Pass features through fully connected layers
Use sigmoid activation in the final layer for binary classification
Step 4: Training and Evaluation
Train the model using binary cross-entropy loss
Evaluate performance using accuracy, precision, and recall
Step 5: Pneumonia Severity Categorization (if predicted positive)
if *Prediction = Pneumonia* **then**
    Segment lungs using Gaussian blur, thresholding, and contour extraction.
    Generate lung mask from segmented region
    Calculate lung opacity as the mean intensity of non-zero pixels within the lung mask
    Predict severity using trained ML model on opacity value
    Map predicted class to severity: {0 → Mild, 1 → Moderate, 2 → Severe}
end
Step 6: Output
Display the predicted classification and severity level (if applicable)

3.6 Classification of Pneumonia into categories

To establish the severity of pneumonia from chest X-ray images, the first step is to segment the lung area by transforming the original image to grayscale, resizing it to 300×300-pixel dimension, and applying Gaussian blur to reduce noise interference. Binary thresholding is subsequently applied to isolate the darker lung areas, followed by contour extraction to outline the boundaries of the lung. A binary mask of the lung is created, and bitwise masking is applied to extract the isolated lung segment area. The lung opacity is then measured by calculating the average intensity of non-zero pixels within the segmented area, where higher values indicate a greater extent of fluid buildup or consolidation. An excel sheet is created using all the pneumonia images in the image set with attributes: image name, Opacity value, Severity level which is defined based on rule-based method. A Decision tree model is trained on this excel data. When a new image is tested, at first it classifies into normal or pneumonia using proposed model, if it is pneumonia then lung opacity is calculated, the calculated opacity value is then fed to the pre-trained decision tree, which is previously trained on labeled data to classify pneumonia severity. Based on the predicted classification (0, 1, or 2), the output is mapped to a human-readable label Mild, Moderate, or Severe Pneumonia and then presented together with the segmented lung image for visual inspection.

4 Results and Discussion

This section illustrates the performance of the suggested model. This includes classification measures and pictorial representation of performance**.**

4.1 Evaluation Metrics

The performance of the models is measured in terms of recall, accuracy, F1-score, precision, confusion matrix and roc curve each of them has a mathematical counterpart formulation and provides different views of a set of model performance factors.

1. Accuracy

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \tag{6}$$

2. F1-Score

$$F1 = 2 \times \frac{Precision \times Recall}{Precision + Recall} \tag{7}$$

3. Precision

$$Precision = \frac{TP}{TP+FP} \tag{8}$$

4. Recall

$$Recall = \frac{TP}{TP+FN} \tag{9}$$

where TP (True positive), TN (True Negative), FN (False Negative), FP (False Positive).

5. Confusion matrix

A confusion matrix is a table that displays the number of true positives, true negatives, false positives, and false negatives in order to provide a summary of the accuracy of a classification model.

6. ROC and AUC score

The performance of a classification model is graphically represented by the ROC curve, which is a plot of the true positive rate versus the false positive rate at various threshold levels.

The overall capacity of the model to separate classes is quantified by the AUC score; a value closer to 1 indicates better performance.

Table 2. Accuracies of Different models.

Model	Accuracy
Neural network	84.93
Pre-trained VGG19 + neural network	89.42
Pre-trained MobileNetv2 + neural network	91.98
MobileNetv2+CBAM+neural network	90.54
ResNet152v2+CBAM+neural network	93.10

Based on same methodology, similar models are trained and tested. Their accuracies are listed above in table 2.

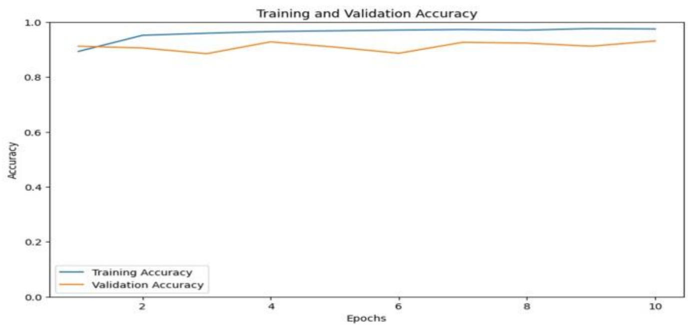

Fig. 5. Training and validation accuracy graph over epochs.

In fig-5, Training and validation accuracy graph over epochs which are obtained from model's experimentation on neural networks for classification are presented.

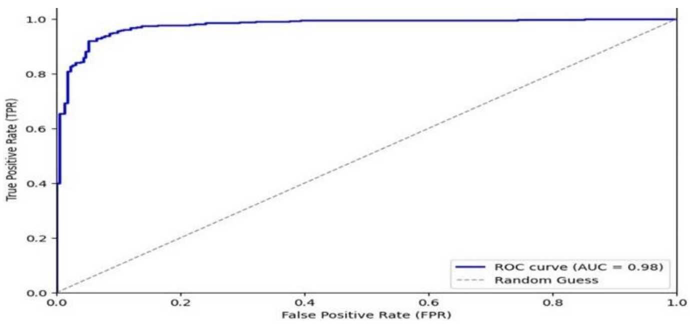

Fig. 6. ROC curve & AUC scores graph.

Fig-6 represents detailed description of ROC curve; model is efficient if the curve reaches the top-left corner and the proposed model achivied 0.98 of AUC score where high values of AUC score represent the effectiveness of the proposed model.

Classification Report:

	precision	recall	f1-score	support
Normal	0.94	0.87	0.90	234
Pneumonia	0.93	0.97	0.95	390
accuracy			0.93	624
macro avg	0.93	0.92	0.93	624
weighted avg	0.93	0.93	0.93	624

Fig. 7. Classification Report.

Fig-7 is the classification report that includes performance metrics Precision, Recall, F1-Score and accuracy of Normal class and Pneumonia class.

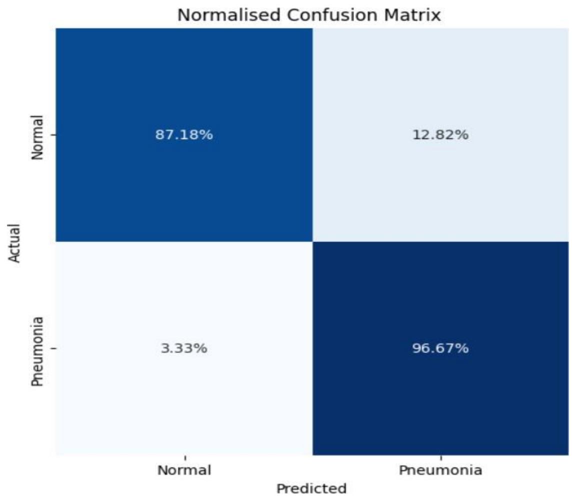

Fig. 8. Confusion matrix of testing data.

Fig-8 represents the confusion matrix of model on testing data. 87.18% of Normal class images and 96.67% of Pneumonia class images are correctly classified.

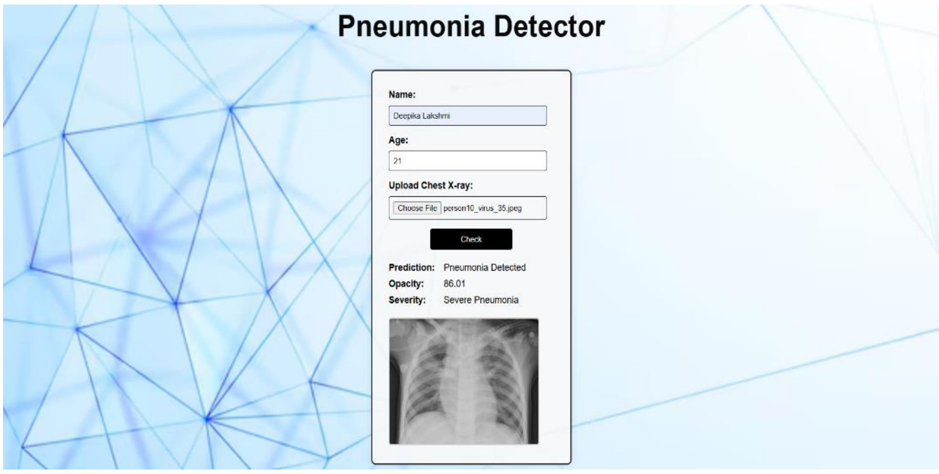

Fig. 9. Web Interface integrating with the proposed model.

Fig-9 represents the web interface that is designed based on the proposed model for easy accessibility.

Table 3. Comparison of Existing Models.

Model	Accuracy
ResNet101+CBAM [19]	82.85%
DenseNet121[13]	83%
VisionTransformer(ViT)+ dynmic mapping reattention [8]	86.73%
EfficientNet based U-Net + ResNet based U-Net [11]	90%
ResNet152V2 + CBAM + Neural Network (proposed)	93.10%

Table 3 shows the above are the existing models that are compared with the proposed model of ResNet152v2 combining with Convolutional Block Attention Module.

5 Conclusion

This study demonstrates the efficiency of Resnet152v2 model combined with CBAM attention for pneumonia diagnosis, attaining high classification accuracy. The model improves feature extraction, increasing the accuracy of the diagnosis by integrating deep learning and attention mechanism and categorizes into categorization of pneumonia into classes. The web-based application further guarantees usability and accessibility increasing the applicability of AI-driven diagnostics in healthcare. Finally, this method improves patient outcomes by reducing the need for manual interpretation, minimizing diagnostic errors and facilitating early identification. The future research can focus on integrating more medical imaging modalities for wider applications, expanding the dataset and improving model efficiency. Although this study has limitations also, it achieves only 93.10% accuracy. Using more advanced models in

CNN's may achieve accurate diagnosis. Including more training images may also achieve good accuracy. These limitations should be addressed in the future work.

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