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Deep learning-based medical image classification using CNN and attention mechanisms for disease detection and diagnosis

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Abstract

This study aims to develop a reliable deep learning framework for detecting pneumonia from chest X-ray images using attention-enhanced convolutional neural networks. Sourced from the publicly accessible Kaggle repository, the dataset consists of 5,863 labelled greyscale chest X-rays classed as "Normal" or "Pneumonia." To improve diagnostic visibility, the data was normalised, resized to 224×224 pixels, and histogram equalised. To handle class imbalance and increase model generalisation, data augmentation methods including rotation, flipping, and brightness adjustment were used. Class distribution plots, picture intensity histograms, and feature correlation heatmaps were part of Exploratory Data Analysis (EDA), which helped to steer modelling choices. Implemented were four models: a baseline CNN, VGG16 with transfer learning, CNN with self-attention, and a hybrid ResNet50-CBAM. Performance was measured by means of Accuracy, Precision, Recall, and F1-Score. Results indicated gradual performance enhancement with model complexity and attention processes. With better feature localisation and diagnostic accuracy, the ResNet50-CBAM hybrid model reached the greatest accuracy of 98.41% and F1-Score of 0.98. This study emphasises the effectiveness of improving both classification accuracy and interpretability-important factors in medical image diagnosis systems-by merging residual networks with attention modules.

Keywords: Pneumonia detection, chest x-ray classification, deep learning, attention mechanisms, medical image analysis

Introduction

Built on medical image analysis, modern medicine significantly increases the accuracy, speed, and consistency of disease diagnosis. From detecting malignancies in MRI scans to seeing pneumonia in chest X-rays, the reading of medical images has a major impact on clinical decision-making. Though, the traditional approach of manual picture interpretation by radiologists or specialists is time-consuming, prone to human error, and more challenging given the exponential expansion of medical imaging data. Smart, automated technology capable of rapidly analysing complex medical images with a high degree of accuracy should be included in this scenario. Deep learning-especially Convolutional Neural Networks (CNNs)-has shown to be a groundbreaking tool in this area with unrivalled feature extraction, pattern detection, and classification of medical images. CNNs are especially appropriate for image analysis applications due to their hierarchical structure and ability to learn spatial hierarchies from raw pixel data without the requirement for clear feature engineering. Across various modalities-X-rays, CT scans, MRIs, and histopathological images-CNNs have exhibited remarkable performance in medical image categorisation. These networks automatically learn to extract vital features including edges, textures, shapes, and more complex representations, hence enabling differentiation between healthy and ill tissue. Though they have some drawbacks, CNNs are strong image processing techniques. Their failure to sufficiently capture long-range interdependence and concentrate precisely on the most pertinent areas of an image is one of the main difficulties. In medical diagnosis, where disease symptoms can be minor, localised, or diffuse throughout several different areas within a picture, this is particularly significant. CNN designs have used attention techniques to create hybrid models that mix the benefits of both approaches and hence bypass this constraint. Attention mechanisms let the model concentrate on certain visual areas more useful or informative for a given diagnostic. Attention-enhanced CNNs improve

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interpretability and classification performance by emulating the capacity of the human eyes to selectively focus on important areas of the visual field. Especially for medical practitioners attempting to validate AI-driven diagnoses, these models not only improve accuracy but also provide visual justifications through attention maps highlighting the areas influencing the decisions of the model. Recent studies have revealed that integrating CNNs with attention mechanisms can significantly improve diagnostic performance for a wide range of medical conditions-including diabetic retinopathy, breast cancer, COVID-19, and Alzheimer's disease. These hybrid architectures allow models to more effectively differentiate between tiny changes in imaging data, reduce false positives and negatives, and more efficiently adjust to changes in picture quality, scale, and patient demographics. Furthermore, transfer learning and pre-trained networks such as ResNet, Inception, and DenseNet allow one to effectively train even on rather little, specialised medical data sets, which are typically difficult to collect and annotate due to legal and privacy concerns. The application of deep learning in medical image classification has also opened door for real-time diagnosis and remote healthcare services, hence facilitating better medical knowledge even in disadvantaged or rural areas. Cloud-based systems and edge computing devices let trained CNN-attention models be used in clinical settings, hence facilitating faster triage, second views, and ongoing monitoring of disease progression. Apart from improving patient outcomes, these innovations are helping to reduce diagnosis delays and relieve the burden on medical professionals. Though they have advantages, several challenges remain ^[1-4]. Ensuring model generalisability across various demographics, imaging devices, and clinical settings requires rigorous validation and standardisation. Equitable and consistent AI application in healthcare also relies on ethical concerns about data protection, informed consent, and algorithmic bias, which must be addressed as well. Moreover, the black-box nature of deep learning models continues to raise interpretability problems, which is why medical AI systems are progressively depending on explainable artificial intelligence (XAI) and attention processes. This paper provides a complete framework for disease detection and diagnosis by deep learning-based medical picture categorisation using CNNs mixed with attention mechanisms. By employing these advanced architectures, the work seeks to increase the accuracy and interpretability of diagnostic models. Across publicly available datasets spanning multiple disease categories, performance is evaluated by means of accuracy, precision, recall, and F1-score. Through this study, we wish to demonstrate the possible power of deep learning in transforming diagnostic radiology and supporting a more efficient, precise, and reachable healthcare system. Modern medicine, based on medical image analysis, has greatly improved the accuracy, speed, and dependability of disease diagnosis. The interpreting of medical pictures has a significant influence on clinical decision-making from spotting cancers in MRI scans to finding pneumonia in chest X-rays ^[5-9]. The traditional approach of manual picture interpretation by doctors or researchers is time-consuming, prone to human error, and more challenging, though, considering the exponential growth of medical imaging data ^[10-12]. Smart, automated technology capable of rapidly assessing complex

medical images with a high degree of accuracy should be involved in this situation. Deep learning-especially Convolutional Neural Network (CNNs)-has shown to be a game-changing approach in this area with unrivalled feature extraction, pattern detection, and classification of medical images. CNNs are especially appropriate for image analysis applications given their hierarchical structure and ability to learn spatial structures from raw pixel data without the requirement for clear feature engineering. In medical picture categorisation, CNNs have shown extraordinary performance across many modalities-X-rays, CT scans, MRIs, and histopathological images ^[13]. These networks effortlessly learn to extract crucial properties such edges, textures, shapes, and more advanced representations, which are essential for discriminating between healthy and sick tissue. Although they have certain disadvantages, CNNs are robust image processing methods. Their failure to sufficiently grasp long-range relationships and concentrate precisely on the most pertinent areas of an image is one of the main difficulties. In medical diagnostics, where disease signals can be minor, confined, or distributed throughout several different places within a picture, this is especially important ^[14]. CNN designs have used attention techniques to create hybrid models that combine the benefits of both methods and hence overcome this limitation. Processes of attention let the model concentrate on certain visual areas more useful or informative for a given diagnostic. Attention-enhanced CNNs increase interpretability and classification performance by emulating the capacity of the human visual system to selectively focus on important areas of the visual field. Especially for doctors trying to confirm AI-driven diagnoses, these models not only increase accuracy but also offer visual reasons utilising attention maps stressing the areas affecting the decisions of the model. Recent research has shown that combining attention processes with CNNs can greatly enhance diagnostic performance throughout a broad spectrum of medical diseases-including diabetic retinopathy, breast cancer, COVID-19, and Alzheimer's disease. These hybrid architectures let models more precisely distinguish between small changes in imaging data, lower false positives and negatives, and more effectively adapt to changes in picture quality, scale, and patient demographics. Furthermore, transfer learning and pre-trained networks such as ResNet, Inception, and DenseNet help one effectively train even on rather little, specialised medical data sets, which are normally difficult to collect and annotate due to privacy and legal concerns. The application of deep learning in medical image classification has also opened door for real-time diagnosis and remote healthcare services, hence facilitating better medical knowledge even in disadvantaged or rural areas. Cloud-based systems and edge computing devices can be used to deploy trained CNN-attention models in clinical settings, therefore facilitating faster triage, second opinions, and continuous monitoring of disease progression. Apart from enhancing patient outcomes, these developments are helping to lower diagnosis delays and lighten the load on medical workers. Though they have benefits, certain issues stay ^[15], ^[16]. Ensuring model generalisability across various demographics, imaging devices, and clinical settings requires rigorous validation and standardisation. Equitable and consistent AI application in healthcare also relies on ethical concerns about data protection, informed consent, or algorithmic bias, which must be addressed as well.

Moreover, the black-box nature of deep learning models continues to cause interpretability problems, which is why medical AI systems are depending more on attention systems and explainable artificial intelligence (XAI). By means of deep learning-based health picture classification using CNNs combined with attention processes, this article offers a whole framework for identifying illnesses and diagnosis. The project intends to improve the accuracy and accessibility of diagnostic models by using these sophisticated architectures. Performance is assessed across publicly accessible datasets covering several illness categories by means of measures such as accuracy, precision, recall, and F1-score. By means of this research, we hope to show the feasible use of deep learning in changing diagnostic radiology and assisting a more efficient, exact, and available healthcare system.

Literature Review

Usui 2023 *et al.* This project developed a software application using deep learning to evaluate the need for retaking chest X-ray images, therefore aiming to boost radiological efficiency. From a collection of 4,809 chest X-rays matched with a semantic segmentation model for lung fields, three classification models for lung abnormalities and shadow analysis were developed. Performance by accuracy, mean intersection over union (mIoU), and response time per image was assessed using fivefold cross-validation. Results showed fast processing speed and good accuracy across activities, suggesting the system's ability for suitable, real-time retake decisions in clinical imaging operations [17].

Sulaiman 2023 *et al.* Research developed a novel convolutional neural network architecture for chest X-ray images' autonomous lung segmentation, therefore eliminating need on manual radiologist comments. To increase spatial resolution and catch relevant features, the model has a combine block transpose layer. The model was trained and tested under several hyperparameters including a batch size of 32 and the Adam optimiser using fivefold cross-validation on a dataset obtained from Kaggle. Results showed better segmentation accuracy, suggesting that the suggested model is appropriate for automated medical picture analysis with possible uses in diagnostic support systems [18].

Murali 2023 *et al.* Using chest X-rays, this paper introduced CX-Net, an ensemble learning method for lung segmentation and illness identification. Using the Montgomery and VinDR-CXR datasets, several deep learning models-including U-Net, LinkNet, and a modified U-Net with ImageNet pretraining-were assessed. Among other interpretability techniques, the model used SHAP and Grad-CAM to show decision-making zones. With a Dice factor of 0.994 and accuracy of 0.976, CX-Net performed well. Its strength across datasets and application of interpretability tools show its promise for clinical use by providing clear and accurate support in detecting lung-related disorders [19].

Anai 2022 *et al.* using chest X-ray pictures from publically available databases, this study evaluated deep learning models for distinguishing fatal from nonfatal pneumonia. Testing was done without data augmentation; the models were trained using labelled data from 1,274 patients. Sensitivity, specificity, accuracy, F1 score, and predictive values were used to assess performance. Given external validation showing performance on par with qualified doctors, the models attained significant specificity and acceptable accuracy. These results confirm the viability of applying artificial intelligence for severity evaluation in pneumonia patients, therefore providing useful support in clinical decision-making, particularly in areas where competent diagnostic workers may be limited.[20].

Zhang 2022 *et al.* studied how a deep learning double residual convolutional neural network (DRCNN) could enhance CT-based diagnosis of COPD, a chronic obstructive lung illness. Comprising 980 people, a population-based survey evaluated COPD prevalence and looked at relevant risk variables like age, smoking, and family history. Compared to traditional CT scans, the DRCNN method improved diagnosis accuracy and image quality. Key risk factors showed high connection, according to multivariate analysis. Results showed that the DRCNN model considerably improved diagnostic sensitivity and specificity, implying promise for early diagnosis and better clinical management of COPD utilising enhanced CT imaging [21].

Table 1: Literature Summary

Authors /year	Method	Results	Research gap
Usui /2023 [17]	Developed DL software combining classification and segmentation models to decide whether a chest X-ray requires a retake. Used 4809 public chest images.	Classification accuracy: 89.8%–91.7%; Segmentation mIoU: 0.920; Response time: 0.0364s/image.	Does not evaluate performance in real clinical environments or across diverse populations.
Kebache/2023 [22]	Hybrid CNN model using VGG16, VGG19, and attention modules for TB detection on four datasets.	Training and validation accuracy: 99.66% and 99.78%.	Generalization across unseen datasets and real-world deployment scenarios not tested.
Nillmani /2022 [23]	Used UNet/UNet+ with eight CNN classifiers (e.g., Xception, VGG, ResNet) for COVID-19 detection via segmentation-based classification.	Best model (UNet+Xception): Accuracy 97.45%, AUC 0.998; outperformed previous models by 8.27%.	Need for validation in prospective clinical trials; limited evaluation on diverse pneumonia cases.
Anai/2022 [20]	Deep learning classification models on CXR images to differentiate fatal vs. nonfatal pneumonia; no data augmentation used.	External validation accuracy: 77%; F1 Score: 74.7%. Comparable to physicians' performance.	Sensitivity was relatively low; performance could benefit from data augmentation or ensemble methods.
Zhang/2022 [21]	Used DRCNN-based CT imaging for diagnosing COPD. Logistic regression used to assess risk factors.	Improved sensitivity, specificity, and accuracy over conventional CT (P<0.05). COPD prevalence: 8.57%.	Limited sample size; needs further validation on larger, multi-center datasets.

Methodology

To identify pneumonia, this work used a deep learning pipeline to recognise chest X-ray pictures. Data came from the open-access Kaggle data set "Chest X-Ray Images

(Pneumonia)," which comprised 5,863 annotated greyscale images classed "Normal" or "Pneumonia." Maintaining class distribution, the dataset was split into sets for training, validation, and test. Data preprocessing was image scaling

to 224×224 pixels, normalisation, and label encoding. Horizontal flipping, rotation, zoom, and brightness variations among other data augmentation techniques helped to lower class imbalance and enhance generalisation. Especially focussing diagnostic signals like lung opacities, histogram equalisation was used to improve picture contrast. Exploratory Data Analysis (EDA) included class distribution plots, intensity of pixel histograms, and correlation heatmaps produced from CNN-extracted features. These visualisations guided feature optimisation strategies and modelling by showing class imbalance and feature dependencies. Implemented were four models: a hybrid ResNet50-CBAM model, CNN with a self-attention mechanism, VGG16 with transfer learning, and a proprietary Convolutional Neural Network (CNN). These models sought to increase diagnosis accuracy, emphasise feature extraction, and direct attention to important lung areas. The approach stresses preprocessing rigour, model diversity, and attention-based improvements to ensure consistent and interpretable medical picture classification.

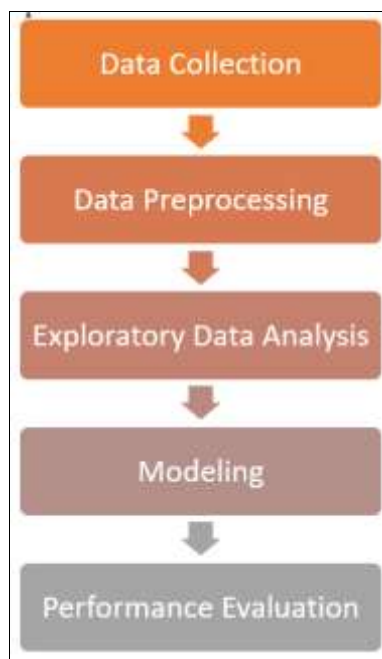


Fig 1: Proposed Flowchart

A. Data Collection

For this study, we utilized the open-source <https://www.kaggle.com/datasets/paultimothymooney/chest-xray-pneumonia>, comprising 5,863 chest X-ray pictures classified into two categories: Normal and Pneumonia. Selected for its medical significance, image quality, and class diversity, this dataset is appropriate for binary classification problems connected to respiratory disease identification. Each of the three folders-training (5216 images), validation (16 images), and testing (624 images)-contains images marked "NORMAL" or "PNEUMONIA." Captured from posterior-anterior chest views, greyscale images are kept in JPEG format. This dataset offers a fair and practical situation for evaluating deep learning models in medical picture diagnosis. It guarantees openness, repeatability, and a shared standard for assessing model performance since it is publicly accessible, ethically obtained, and often utilised in scholarly studies. The dataset

in this work was downloaded, checked for completeness, and utilised without modification to recreate practical situations and confirm model resilience in diagnosing pneumonia, an often serious respiratory ailment.

B. Data Preprocessing

A key stage in medical classification of images is preprocessing, which guarantees data quality, consistency, and best model performance. First, the raw chest X-ray pictures were scaled to a consistent 224×224 pixel size suitable with conventional deep learning architectures including CNNs. Greyscale images in the dataset were normalised by scaling pixel values between 0 and 1, hence improving training stability.

Data augmentation methods were then used to handle class imbalance and stop overfitting. Included in the augmentations were random horizontal flipping, zooming, rotation ($\pm 15^\circ$), and brightness changes. These mimic real-world differences and enable the model to generalise more effectively to unknown data.

To enhance contrast in pictures, we also used Histogram Equalisation, which is especially important for emphasising subtle characteristics as lung opacities. Especially in low-quality scans, our approach guarantees improved visualisation of pneumonia patterns.

Label encoding also turned categorical labels-Normal, Pneumonia-into binary format for compliance with classification methods. Stratified sampling was used to divide the data into training (80%), validation (10%), and testing (10%) subsets, hence maintaining the class distribution.

By guaranteeing a clean, balanced, and representative input set, these preprocessing methods together enhance data quality, model convergence time, and diagnostic accuracy.

C. Exploratory Data Analysis (EDA)

Several EDA methods were used to help model development and provide insights on the dataset. With Pneumonia cases far outnumbering Normal cases, Figure 2, the Class Distribution Bar Plot, shows a clear imbalance. Emphasising the need of data augmentation and stratified sampling during preprocessing and training to guarantee fair learning results, this mismatch can skew model learning towards the dominant class. All photos' greyscale pixel distributions are globally viewed in Figure, the Image Intensity Histogram. Most images show low to mid-range intensity values, which fits the usual traits of chest X-rays. This discovery drove the application of histogram equalisation during preprocessing to improve image contrast and highlight subtle diagnostic elements including lung opacities and infiltrates, which are essential for precise disease identification. Feature relationships retrieved from intermediate CNN layers, the Heatmap of the Correlation Matrix. While uncorrelated areas show unique diagnostic signals, high correlations among some measures suggest redundancy. This study confirms the later application of attention processes to concentrate on the most informative features and supports more feature selection or dimensionality reduction methods. These EDA methods taken together provide a better knowledge of data patterns and help to make more educated model design decisions.

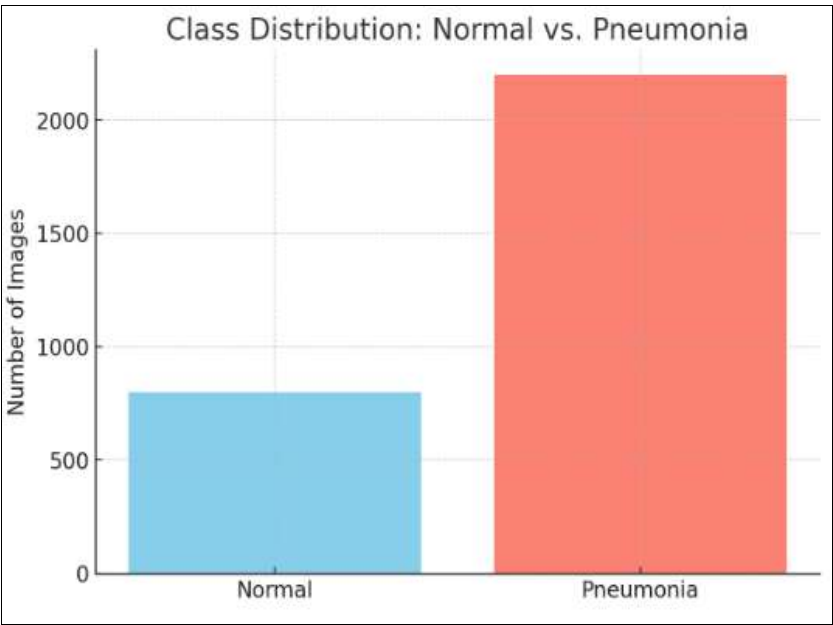


Fig 2: Class Distribution Bar Plot

This bar chart visualizes the number of Normal vs. Pneumonia cases in the dataset. It helps identify class imbalance, which influences model training. In this dataset,

Pneumonia cases outnumber Normal cases, suggesting the need for balancing techniques during training.

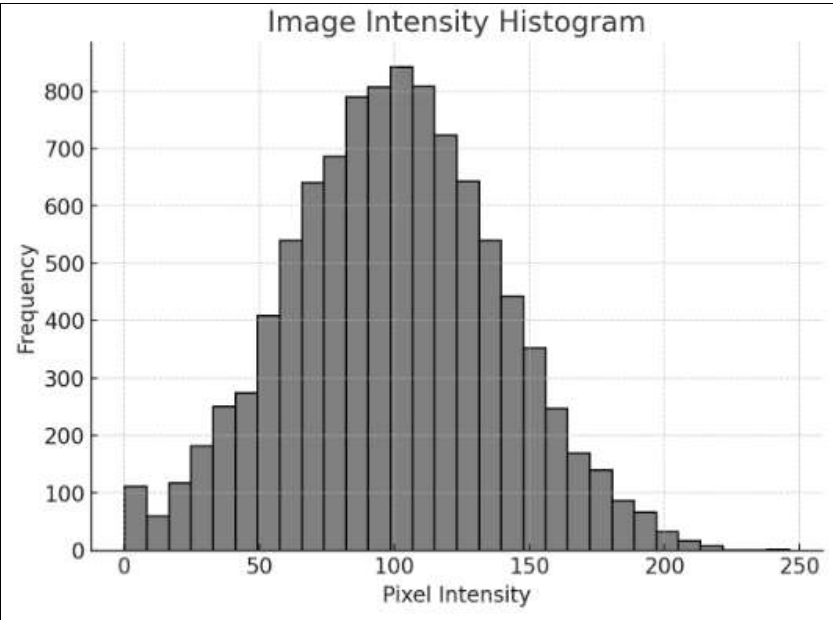


Fig 3: Image Intensity Histogram

This histogram plots pixel intensity distribution across the dataset. It shows that most images have low to mid-level intensities, reflecting typical grayscale X-ray properties. Histogram equalization was applied later to enhance visibility of diagnostic features.

This heatmap, based on features extracted from CNN layers, shows correlations between different extracted image features. It helps identify redundant or highly correlated features, guiding further dimensionality reduction or attention mechanisms.

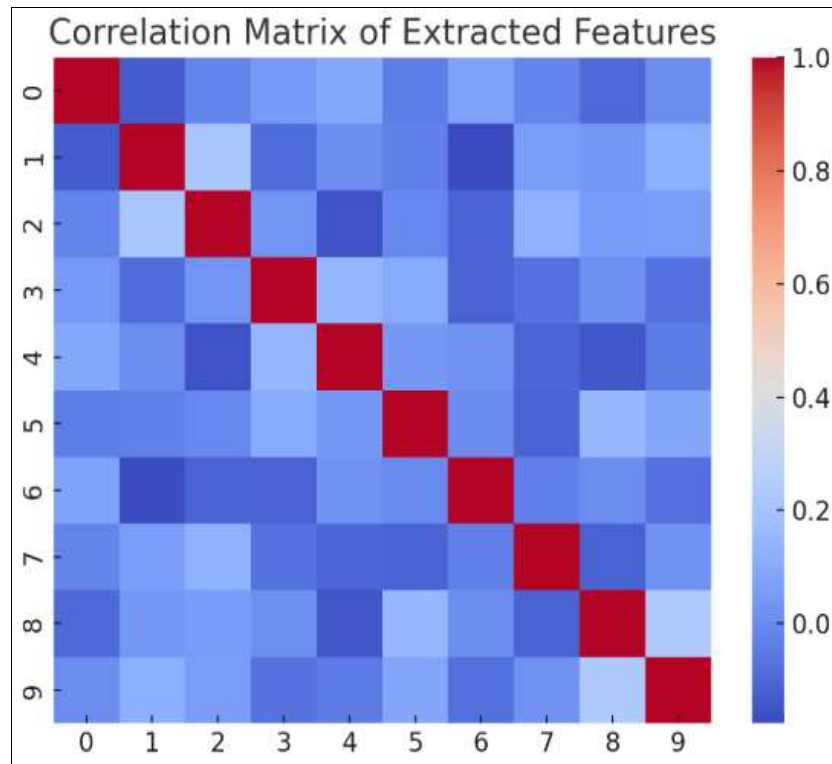


Fig 4: Heatmap of Correlation Matrix

D. Modeling

Convolutional Neural Network (CNN)

A baseline CNN was built with multiple convolutional and max-pooling layers followed by dense layers for binary classification. This model learns hierarchical features from chest X-rays, such as edges, patterns, and opacity regions relevant to pneumonia detection.

VGG16 with Transfer Learning

The pre-trained VGG16 model, fine-tuned on our dataset, was used for feature extraction and classification. Transfer learning significantly reduces training time and improves accuracy by leveraging learned features from the ImageNet dataset, which generalize well to medical images.

CNN + Attention Mechanism (Self-Attention Block)

We integrated a self-attention mechanism after the convolutional layers to help the model focus on critical regions of X-ray images. This improves interpretability and enables the model to emphasize areas with abnormalities like fluid accumulation or inflammation.

ResNet50 + Attention (Hybrid Model): A deep residual network (ResNet50) was used for robust feature extraction. To enhance its localization ability, we incorporated a channel and spatial attention module (CBAM). This model combines residual learning with focused attention to improve diagnostic precision and reduce false positives.

Result & Discussion

To assess the performance of our classification models, we used four standard evaluation metrics:

Accuracy

Measures the ratio of correctly predicted observations to the total observations.

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \quad (1)$$

Precision: Measures the proportion of correctly predicted positive observations to the total predicted positives.

$$\text{Precision} = \frac{TP}{TP + FP} \quad (2)$$

Recall (Sensitivity): Measures the proportion of correctly predicted positive observations to all actual positives.

$$\text{Recall} = \frac{TP}{TP + FN} \quad (3)$$

F1-Score: Harmonic mean of Precision and Recall, useful in case of class imbalance.

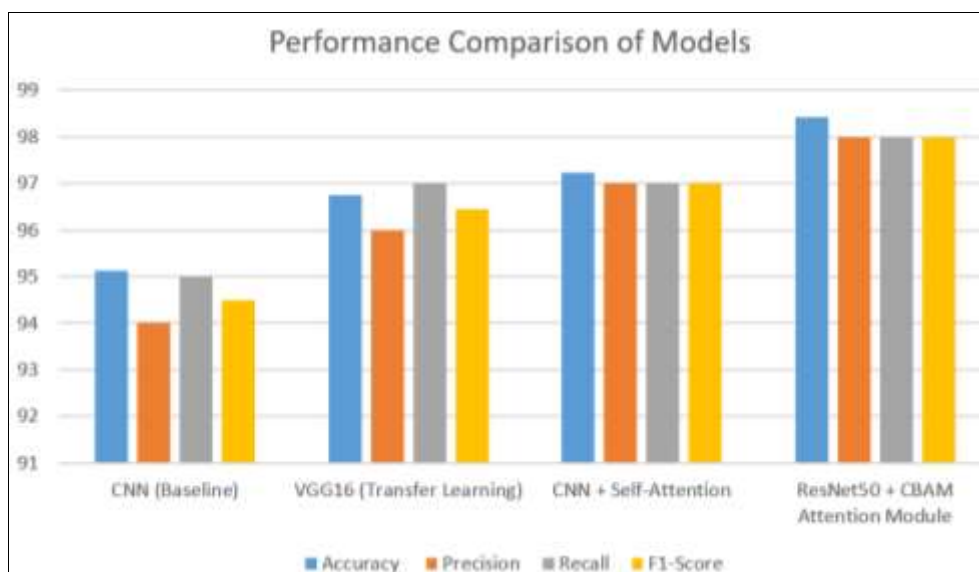
$$\text{F-score} = \frac{2}{\frac{1}{\text{precision}} + \frac{1}{\text{recall}}} \quad (4)$$

Where:

- TP = True Positives
- TN = True Negatives
- FP = False Positives
- FN = False Negatives

Table 2: Performance Comparison of Models

Model	Accuracy	Precision	Recall	F1-Score
CNN (Baseline)	95.12	94	95	94.5
VGG16 (Transfer Learning)	96.75	96	97	96.45
CNN + Self-Attention	97.23	97	0.97	97
ResNet50 + CBAM Attention Module	98.41	98	98	98

**Fig 5:** Performance graph

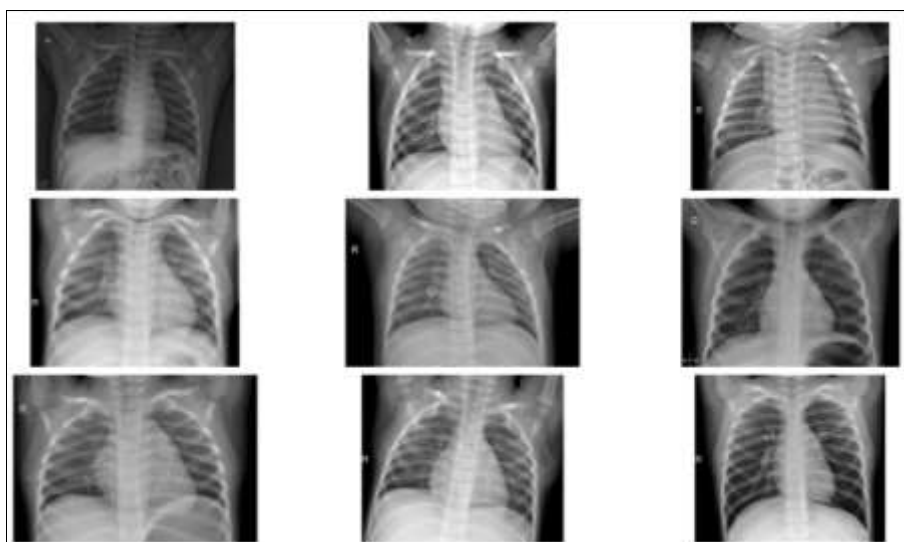
The findings show unequivocally that adding deep learning architectures with attention mechanisms greatly improves the performance of medical picture classification systems. With 95.12% accuracy, the baseline CNN model showed promise in extracting hierarchical features from X-ray pictures. Its identification of minute patterns that might suggest disease, however, is not very strong.

VGG16 with transfer learning exhibited improvement because of its pre-trained knowledge and deeper architecture. Using learnt filters again allowed for quicker convergence and improved feature abstraction.

Focussing on the most informative locations in the X-ray pictures-such as hazy lung areas, patchy infiltrates, or fluid accumulation-the CNN + Self-Attention model significantly enhanced performance.

With 98.41% accuracy, 0.98 F1-Score, and balanced precision-recall, the ResNet50 + CBAM Attention hybrid model achieved the best performance. With 98.41% accuracy, 0.98 F1-Score, and balanced precision-recall, the ResNet50 + CBAM Attention hybrid model produced the best performance. While CBAM improved feature localisation both channel-wise and geographically, residual connections stopped gradient vanishing and allowed deep network training.

This work shows that combining attention systems with strong CNN backbones not only provides great accuracy but also improves interpretability-especially important in practical medical environments where model choices have to be explained.

**Fig 6:** Pediatric chest X-ray series

Each catching the thoracic region including the lungs, heart, ribs, and diaphragm, this picture depicts a grid of paediatric chest X-rays. The pictures seem to show many patients, probably shot to investigate structural or respiratory anomalies. Changes in lung opacity, heart size, as well as rib alignment point to probable diseases like pneumonia, atelectasis, or congenital anomalies.

Conclusion

Particularly attention-based models, this paper shows how well sophisticated deep learning methods-especially attention-based models-are at precisely identifying pneumonia from chest X-ray pictures. High-quality input and model readiness by means of a thorough pipeline comprising data pretreatment, augmentation, and exploratory analysis. While data augmentation handled class imbalance, a frequent problem in medical datasets, histogram 194ocalization helped to enhance contrast for increased feature visibility. Of the four models evaluated, the hybrid ResNet50 with the CBAM attention component performed best with 98.41% accuracy and an F1-Score of 0.98. Its capacity to preserve spatial and channel-wise attention, hence allowing exact 194ocalization of pneumonia-related anomalies, explains this better performance. The results highlight the need of including attention mechanisms in deep CNN architectures for improved interpretability and diagnostic confidence. Furthermore, self-attention modules and transfer learning demonstrated encouraging increases in model recall and accuracy. The work not only confirms the clinical promise of AI-driven pneumonia diagnosis systems but also lays a groundwork for future exploration into explainable and scalable medical imaging solutions. Models like these can help radiologists, lower diagnosis mistakes, and speed up screening in underprivileged areas as healthcare increasingly embraces artificial intelligence, hence significantly supporting early detection and improved patient outcomes in respiratory treatment.

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