Nigerian Journal of Technology (NIJOTECH)
SI-2026A: Advances in Modelling, Simulation, and AI/ML for Multi-Disciplinary Engineering Applications, *2026. pp. 1- 13*
www.nijotech.com

Print ISSN: 0331-8443
Electronic ISSN: 2467-8821
https://doi.org/10.4314/njt.2026.5954SI

OPTIMIZED DEEP LEARNING APPROACH FOR PNEUMONIA DETECTION USING CHEST X-RAY IMAGES

AUTHORS:
G. Deshmuk[1], V. Kulkarni[1], V. U. *Rathod[2], A. Pawar[1], A. Chhajed[3] and V. Ghonge[3]

AFFILIATIONS:
[1]Department of Computer Engineering, Pimpri Chinchwad College of Engineering Affiliated to Savitribai Phule Pune University, Maharashtra, INDIA
[2]Department of Computer Science and Engineering (Artificial Intelligence and Machine Learning), Vishwakarma Institute of Technology, Pune, Maharashtra, INDIA
[3]Department of Computer Science and Engineering (Software Engineering), Vishwakarma Institute of Technology, Pune, Maharashtra, INDIA

***CORRESPONDING AUTHOR:**
Email: vijay.rathod25bel@gmail.com

ARTICLE HISTORY:
Received: November 11, 2025.
Revised: February 21, 2026.
Accepted: March 18, 2026.
Published: Early view

KEYWORDS:
Pneumonia, Classification, Deep Learning, Convolution Neural Network (CNN), Neural Networks, EfficientNetB3 Architecture, Radiological X-Ray Images, Detection.

ARTICLE INCLUDES:
Peer review

DATA AVAILABILITY:
On request from author(s)

EDITORS:
Sagar Shelare

FUNDING:
None

Abstract

Pneumonia is a virus that ranges from moderate to severe in that there is inflammation of the air sacs located in the lungs, the symptoms of which are fever, cough and difficulty in breathing. Pneumonia may be due to bacteria or viruses. Treatment will generally be by means of antibiotics or antiviral medicines, according to the cause. Preventive medicine would consist of vaccination and good hygiene. Deep learning, a subset of artificial intelligence, has proved to be a mainstay for the development of predictive models. Detection of pneumonia may be made by many methods, such as CT and pulse oximetry, but X-ray tomography is the method mostly employed. The interpretation of chest X-rays (CXR) is an inherently subjective process. In this study we investigate the field of pneumonia lung classification, using images of CXR. The data set consists of 5863 images all of which are labeled as pneumonia positive and normal. This work confines itself to a particular anatomical region as regards the analysis of the disease, so that therefore the performance of pneumonia detection will be studied in detail. The study focuses on the comparative analysis of deep learning models with special emphasis on traditional CNN as compared to techniques of Transfer Learning such as Inception Net, VGG16 and ResNet. The implementation suggested underlines a granular understanding of model effectiveness which was able to jointly reveal that CNN using EfficientNetB3 architecture resulted in higher performance characteristic to pneumonia detection for the dataset selected. We highlight, through intensive experimentation and relative comparisons, the advantages of leveraging base frameworks of CNNs rather than transfer learning paradigms in the specific detection of pneumonia from CXR. The designed CNN architecture has also achieved a commendable accuracy rate of 99.60% compared to other deep learning techniques and existing models on the same dataset.

HOW TO CITE:
Deshmuk G., Kulkami V., Rathod V. U., Pawa A., Chhajed A. and Ghonge V. "Optimized Deep Learning Approach for Pneumonia Detection using Chest X-Ray Images", *Nigerian Journal of Technology*, SI-2026A: Advances in Modelling, Simulation, and AI/ML for Multi-Disciplinary Engineering Applications, 2026. pp. 1 - 13. https://doi.org/10.4314/njt.2026.5954SI

1.0 INTRODUCTION

Pneumonia is an acute infection of the lungs resulting in sent in a semi-sentient state of cough. Pneumonia is one of the deadliest illnesses. There are two main types: bacterial and viral. However, the symptoms tend to be more serious for bacterial pneumonia, and it requires antibiotic treatment; on the other hand, viral pneumonia generally will get better without treatment. With an estimated global toll of 1.4 million deaths annually in children under the age of 5 due to pneumonia, accounting for 18% of deaths for this age cohort, it is a grave burden in South Asia and sub-Saharan Africa.

Notwithstanding this, pneumonia is preventable with simple things and treatable with simple and inexpensive medical helpp. Pneumonia is a multifaceted disease affecting the lungs, and the various organisms causing it and their manifestations may present difficulties in diagnosis and management. Goes into great detail, discussing the etiology of pneumonia, the many various germ causes in different stages of its pathogenesis, and the diagnostic means in use in diagnosis by the medical profession. The problem of antibiotic resistance is touched upon and advice as to the rational use of antibiotics and the knowledge of the patterns of resistance emerging is discussed with a view to greater enlightenment in treatment. Proper management of community-acquired pneumonia is essential to decrease its deleterious effects [1]. It stresses the importance of the urgent, accurate assessment of the patient to allow alteration of the treatment, so ensuring that no missed out preventable state ensues. The introduction of AI in radiology, as introduced within [2], is a huge advance in the diagnosis of pneumonia. Possibly the interpretation of the images is going to obtain a boost in its precision, thus revolutionizing clinical practice and improving the end results for the patient, and these include the diagnostic work patterns taken primarily by AI and deep learning. Advice to those involved in the vagaries of diagnosis and treatment of pneumonia by the clarification of AI [3] might be viewed as a considerable help in the management of pneumonia in the adult patient.

This discussion may range from symptom evaluation, imaging modalities, and selection of antibiotics. The paper touches upon these with much needed information germane to the improvement of patient care and prevention of complications. Aside from clinical recognition, [4] gives a short discussion of pneumonia tracing its epidemiology, its prevention, and its treatment in efficacious avenues towards the first understanding the multifactorial nature of pneumonia for its prevention and treatment. Viral pneumonia especially of newly emerging viruses such as SARS-CoV-2 present peculiar problems with its diagnosis and treatment. There is given in [4] an extensive account of viral pneumonia reaching from its epidemiology, pathogenesis, and presentation, to its treatment. This paper epitomizes the vital necessity of securing an early diagnosis for the optimization of treatment results and control of the dissemination of the disease.

The use of deep learning has lately rendered the pneumonia detection system on radiological images relevant. The performance of different convolutional neural networks in the area of pneumonia detection in CXR is examined in article [5]. Similarly, article [6] presents a thorough overview of the techniques applied which make use of deep learning, particularly in the area of pneumonia detection. This article presents ample information regarding deep learning networks and these sorts of methodologies, as researchers and practitioners will be able to train themselves properly without going astray to the current state of this new opening of research. In addition to these later papers, papers [7], [8] have also made tremendous contributions to pneumonia diagnosis through deep learning techniques. The named papers run through the portraits of different facets of deep learning instruments employed in pneumonia detection which is based on CXR, and also touching upon aspects of current research difficulties and trends and future directions of pneumonia diagnosis. The studies the different deep learning algorithms that are employed for the detection of pneumonia through CXR, and thus throw much light upon their various uses in diagnosis [9]. On the same lines presents an inquiry into the inner structure of how a deep learning based model is built for the purpose of diagnosis of pneumonia, and enumerates all the evidences that difficulties and hurdles abound in this field according to the present view [9].

In better detail, [10] looks at applications of deep learning models for pneumonia detection from X-rays using different models and learning techniques and indicates possible ways of great use to investigate in this area in the future. Accordingly, this continues with clarifying the application of these paper purposes of diagnosing pneumonia through deep learning models to increase the efficiency and accuracy rates of the detection of pneumonia in CXR. Something similar outlines that the secret of an increase in the survival rates, consists in the making of the first diagnosis, so as to prescribe antibiotics according to the needs, to effect a good purpose. In this connection it must be borne in mind, that if the unfavorable condition is attributable to more than one cause, it is very inconvenient. The main thing is to prescribe the best possible remedies at out, and this will have a great deal to do with limiting the risk of uncontrolled use of antibiotics. Nevertheless, [11] indicates that more

https://doi.org/10.4314/njt.2026.5954SI

research must be done to unravel some hidden facts in regard to the epidemiology and pathophysiology as regards them. Something similar, [12] indicates the application devised by experts to indicate pneumonia in CXR using only a very limited amount of data with a view to making the results of that application considered general, and applicable. [13] Looks into deep learning applications, and especially into CNNs, and the analysis of chest X-rays for the diagnosis of pneumonia.

The main aim and objectives of this research is, deep learning has gained popularity due to its ability to assist with reading chest X-rays without needing human judgment as humans often make poor decisions or take a long time to diagnose pneumonia. CNNs (Convolutional Neural Networks) can autonomously learn to detect important features of an X-ray image and quickly, easily and accurately identify pneumonia. The earlier a person is diagnosed with pneumonia, the greater the chance of recovery and the lower the chance of dying.

This part emphasizes discussing the analysis done on the existing models until now about the prediction per se related to CXR. Proposes the study with the developments of CAD (Computer Aided Diagnosis) utilizing a combination of the deep transfer learning models for enabling precise prediction results on the classification of CXR [14]. A Hybrid Ensemble Approach has been made using a combination of three classifiers which include Google Net, ResNet-18 and DenseNet-121, with the application of the weighted averages, the weights we observed assigned to the classifiers has been taken from the usage of a new method formulated by Kundu R et al. for enabling the prediction of pneumonia. The proposed model has been developed with Adam Optimization Techniques and the Cross-Entropy Function for the inclusion of the parameters peculiar like the learning rate, the image dimensions and the no. of Epochs to be 0.0001, 224*224*3, 30 respectively with F1-Score values of 98.79% & 86.95% on the two data set viz. Kermany and RSNA respectively.

A new hybrid CNN model was proposed [15], wherein VGG16 and VGG19 convolutional neural network models were used as feature extractors to classify images drawn from public CXR images dataset made public by Kermany et al features. The dataset comprised of 1583 images fitting the normal class and 4273 images fitting the Pneumonia class. The analysis depicts that the ensemble classifier is used as an aid for the radiologists in making time-efficient medical decisions for the pneumonia diagnosis in CXR images with 98.55% accuracy and 99.30% recall. In this study proved that there existed advantages of using the CNN model combined with filters, SVM classifier and YOLOv3 to diagnose X-ray images with 99% accuracy and 99% F1-score.

In this research work [16] during his research reported that it is possible for less complex CNN architectures designed from scratch, to easily outperform complex models which use Transfer Learning approach, with an F1-score of 97.4% and AUC = 0.982 with dropout thereafter. In this research work [17] proposed Machine Learning architecture utilizing CNN in detail; in his research it was found that during validation of loss function drastic increments were found during the last 30 iterations; however this function in the end had arrived to a position very close to zero. The proposed architecture can be utilized to classify the X-ray images either as 'Normal' or 'Pneumonia' in help of the medical professionals.

The personalized ResNet model proposed yielded an accuracy of 95% globally for reliable analysis of CXR images which facilitates the process of decision making. The respective F1-score for normal and pneumonia cases was 0.93 and 0.96. The October 2021 study brought forth assist in diagnosis of pneumonia in X-ray images with use of CNN-Transfer Learning approaches. The study yielded a total accuracy of 98.28% with values of precision, recall and F1-scores respectively for normal as 98%, 95% and 96% and in pneumonia as 99%, 99% and 99% [18].

In the study the improvement of accuracy with lower training times has been tackled using the pre-trained models and a combination with the model CNN designed by them. The accuracy achieved using the inception-V3 model was the best among the others, where the accuracies obtained were 99.29%, 98.83%, 99.73%, 99.28% in terms of precision, recall and F1-score.

2.0 RESEARCH DESIGN AND METHODOLOGY

The recommended deep learning model to enable the prediction of pneumonia was developed over a number of systematic stages, these stages consisting of data collection, data cleaning, data augmentation, feature extraction, training, testing, classification, and final prediction. The first dataset obtained was from a

https://doi.org/10.4314/njt.2026.5954SI

publicly available medical-in-image repository-Kaggle-named CXR (Pneumonia), an array in which there existed 5863 X-Ray images in a Mutable Internet File format split into two groups namely normal and Pneumonia. The dataset was grouped into three main folders pertaining to train-test and validation sets. Each of the tricks-test and validation folders possessed sub-folders named Normal and Pneumonia specific, containing the JPEG images. In the operation of image going through the various images in the dataset the operation of preprocessing ensures that these are ultimately joined up with their folders. All three folders containing both of the above-mentioned classes were graphically visualized by histogram so that it could be seen that the Pneumonia images were more numerous in each of the sub-folders. The combination phase of image augmentation necessitated the generation of images and their storage so as to afford more image data to the model in its training phase.

The training data samples were displayed in view of the visualization. The compilation of the model was done correctly with the CNNs with EfficientNetB3 Architecture. The input image was defined to be 224*224. The model was trained for 10 epochs and then validated with the help of validation data. Testing and training of the model were carried out, and the training accuracy and testing accuracy were calculated accordingly. The model was tested in the process of prediction for unseen data for prediction of the class. Based upon the dataset samples, classification reports and confusion matrices were prepared and subsequently interpreted regarding the performance and the results of the model. Similar procedure was adapted to various CNN models like the RESNET and the VGG and the INCEPTION models. The comparative analysis of the performance of the various models showed that the model CNN with EfficientNet3 Architecture was concluded to be the most suitable for classifying the radiological images like X-rays into normal or Pneumonia.

2.1 Proposed Model Design Architecture

The design of the model architecture for the classification of CXR into normal and Pneumonia introduces the feature extractor as 'EfficientNetB3'. EfficientNetB3 is a state of the art CNNs that has been trained on the Image Net weights, which is a great size of dataset that helps the model extract meaningful and bringing features from medical images and also gives a hierarchical structure overall. The model employs images of size 224×224×3 and they are convoluted through a number of convolutional and mobile bottleneck (MBConv) modules of various sizes of kernel (3×3 and 5×5) as previously illustrated in Figure 1. The layers of the base model get frozen during the training process in order to retain the learnt and pressured knowledge, so that no weights are automatically retrained during the training. This helps in an efficient phase of feature extraction while minimizing the computational overheads expected in the process and also mitigate over fitting of the model classes. The trainable layers for classifying pneumonia are added after the base model layers to enable efficient Fine-Tuning of the model for task-related classification. A Batch Normalization layer is included straight after the dense layer in order to stabilize the learning time. This is then followed by a drop-out layer that inhibits random neurons during training to prevent over fitting. At that point, the final dense layer corresponds with the output layer onto which the previously discussed features are mapped into targets on two classes. This technique called hybrid transfer learning provides a significant enhancement in terms of classification accuracy, with computational efficiency. Layers include deep feature extraction through the classification layers fine-tuned according to the model requirements, ensuring good and reliable pneumonia detection from chest X-ray images. In the proposed research work, we create a task-driven hybrid transfer learning model which does not use EfficientNetB3 as a constant pre trained backbone; instead, it allows for selective fine tuning of EfficientNetB3 with custom CNNs, which can provide features that are specific to the pneumonia condition from sweat radiographs. In contrast to modern conventional transfer learning models that utilize mostly pre trained features, the new model uses a combination of domain-specific fine tuning, highly optimized preprocessing, balanced training techniques, resulting in significantly better generalization and an increased accuracy rate of 99.6% over previously developed CNN and transfer learning type approaches from other researchers on the same data set.

The pertained EfficientNetB3 model was originally trained on ImageNet using a set input size of 224 × 224 × 3; the input images must also be resized to match this format. The resize preserves enough spatial and texture information in chest X-ray images so that the computational cost and memory requirements for training models and comparing their performance across all models were as stable as possible.

https://doi.org/10.4314/njt.2026.5954SI

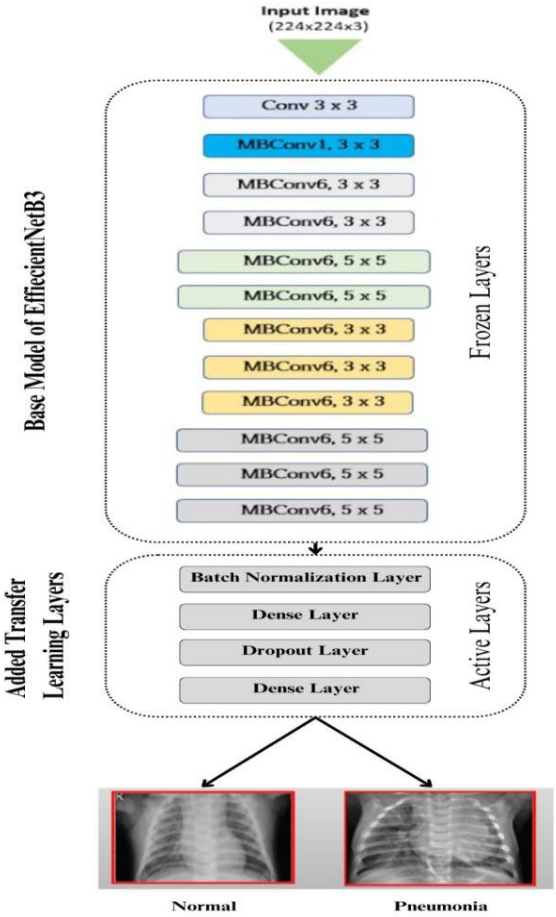

Figure 1: The proposed model architecture of EfficientNetb3 with added active layers

3.0 RESULTS AND DISCUSSIONS

3.1 Implementation Details

To increase its relevance to clinical research, the Kaggle Chest X-ray dataset was chosen as it contains a significant number of labeled, radiographic images using an established standard for benchmarking. Due to class imbalance between the pneumonia and normal groups, class weighting and data augmentation techniques were applied to reduce the chance of biased learning from the data. Stratified sampling methods were utilized to split the dataset into training, validation and testing sets maintaining class proportions to allow for unbiased evaluations of model performance. Although one dataset was used to train the model, different splitting methods and balance techniques were utilized to improve reliability and generalization.

The Pneumonia is one such publicly available dataset present on the Kaggle platform [19], which has been employed in this research paper. The dataset comprises 5,863 images belonging to two baseline classes named Pneumonia images and Normal images. These images are appropriately labeled to enable the process of binary classification to identify if it represents pneumonia and its absence respectively. The first ‘Pneumonia’ class comprises images that are diagnosed with either viral and/or bacterial pneumonia, therefore appropriately defining the pneumonia features. The ‘Normal’ class comprises various images representing normal subjects who do not possess pneumonia features.

All of these images are in JPEG format but of different dimensions, but they are all in gray scales thus the key properties essential for the correct diagnoses of pneumonia are better emphasized. The data set has been divided into a training data set and test data set, with a majority included in the training data set in order to test the results of the designed model without polluting the efficiency of the determinations made. The data set Pneumonia [25] has been pre-processed to some extent, but during model building and

https://doi.org/10.4314/njt.2026.5954SI

experiments, further normalization and modification of the data by means of picture augmentation could take place thus further assisting in the learning process. The data set is the main support of this study and serves as a good background to build a pneumonia predicting model thus allowing for vast coverage in respect to the differences noticeable in the pneumonia and normal chest images.

The Kaggle Chest X-ray dataset (pneumonia) was chosen as it is publicly available, well-annotated, and widely used as a benchmark data set, allowing for a fair comparison to other studies. The size (5863 images) and balanced distribution of images of normal and pneumonia cases also offer enough variability to allow for effective training and evaluation of models. The dataset is sufficiently large to validate the performance of the models, and will provide additional data for the generalizability of a model if it is tested on multiple clinics with different data in subsequent research work.

3.2 Performance Evaluation Metrics

The performance analysis of the models applied to the data is reviewed and compared in terms of different coming measures. These are Accuracy, Precision, F1-Score and Recall. The measures are stated and found from the true label and predicted labels obtained from the models on the dataset. These measures are based upon the following defined terms:

True Positives (TP): The number of instances which are labeled as positive, which predicted to be true of positives.

FP (False Positives): Those samples, which have been predicted as positive, but are negative in the data set.

True Negatives (TN): Those sampled, which have been predicted as negative, but are really negative.
False Negatives (FN): The no. of instances, which have been predictable as negatives, but are really positives.

A matrix can be constructed from the above terms. It represents a logical explanation related to the actual labels and predicted labels. The above-mentioned matrix is referred to as “Confusion Matrix”. This is represented in Table 1. In the case of binary classification models, a 2x2 matrix is constructed to check the efficiency of the model. In ‘N’ classes, an ‘NxN’ matrix has to be constructed.

Table 1: Confusion matrix for performance analysis

Confusion Matrix		**Actual Label**	
		Positive	**Negative**
Predicted Class	Positive	True Positive (TP)	False Positive (FP)
	Negative	False Negative (FN)	True Negative (TN)

The terms in the confusion matrix are later utilized to derive the performance measures defined and formulated below.

3.2.1 Accuracy

Accuracy is the fraction of the total number of correctly predicted samples to the total samples. Accuracy measures the performance of the model.

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

3.2.2 Precision

Precision is measured as correctly predicted positive instances over negative instances. It is calculated as follows: It is the ratio of correctly predicted positive instances to the total instances that are predicted to be positive.

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

3.2.3 Recall

Recall is calculated by taking the formula correctly predicted positive labels / total number of positive labels in the data. The result is the measure that gives the proportion of correctly predicted positive labels to the total positive labels in the data.

Recall = TP/ (TP + FN) (3)

3.2.4 F1-Score

The F1-Score is the harmonic mean value of precision and recall. The F1-Score shows the result of the entire model.

$$F1 = score = 2 * (Precision) * \frac{Recall}{Precision+Recall} \quad (4)$$

The result that can be achieved by an AI model can be judged in terms of performance metrics such as Accuracy, Precision, Recall, and F1-Score. Performance Metrics are also beneficial for making a comparison among various models with respect to their results. A higher value of these factors implies that the result produced is more efficient and precise.

In order to keep the pertained ImageNet features intact, the base layers of EfficientNetB3 were frozen at the beginning of training because they represent general visual elements such as edges, textures, and shapes. The base layers were kept frozen for both the initial training phase to help reduce over fitting and improve convergence times and also so that all that was trained were the newly added classification layers. During the fine-tuning stage, some of the deeper network layers were un-frozen based on how they performed during validation and subsequently trained so that the model could learn features that are specially related to pneumonia.

3.3 Results Analysis

The subsection highlights the models that are applied and the results that are achieved with the proposed model.

3.3.1 CNN with EfficientNetB3 model

The proposed model combined with EfficientNetB3 has yielded great results while classifying the radiology images as Pneumonia or as Normal. All the results are satisfactory and reliable. The results, that we get on the used data set with the application of the proposed model, with values accuracy, precision, recall value, and F1-Score being 99.60%, 99%, 97%, and 98% as shown in Table 1 above. The Figure number 2 is illustrating the improvement we got regarding the accuracy and loss while training the proposed model.

3.3.2 VGG model

The VGG model is built from scratch and tested in the same dataset with low accuracy with respect to the proposed model. The VGG model with an accuracy of 91%, precision of 95%, recall of 91% and F1 score of 93%. The VGG model with 20 epochs might yield low accuracy compared to the proposed model. This is shown in Figure 3 below.

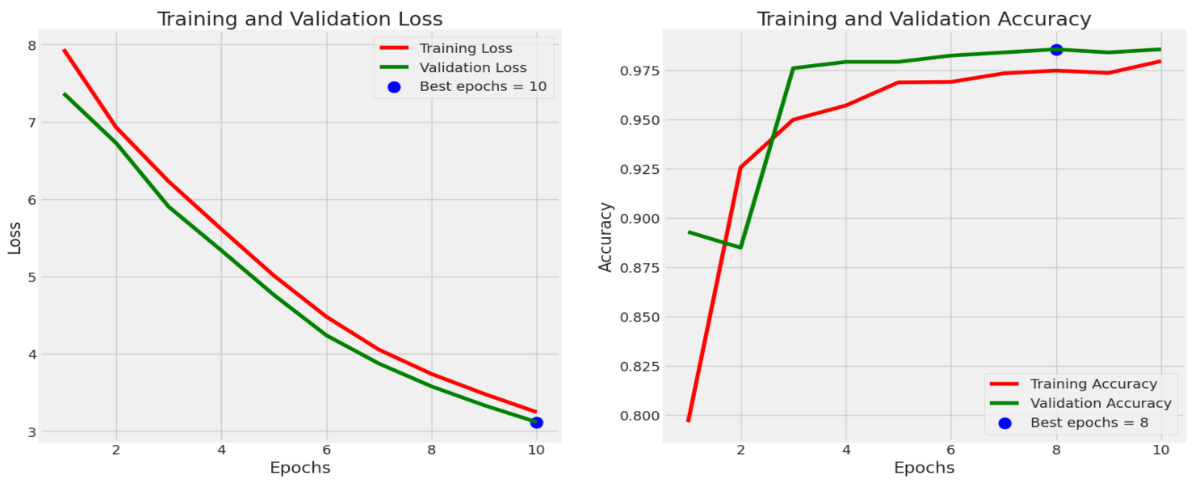

Figure 2: Training loss and accuracy in CNN efficient NetB3 model

3.3.3 INCEPTION model

The dataset [25], while training the model that is present in INCEPTION, has managed to give an accuracy of 94%, precision of 99%, but with a comparatively low recall value of 91% and an F1-Score of 95%. The model was trained on 15 epochs with 187625 trainable parameters that consumed 732.91 KB memory together. The model has complex computation and is quite costly; this has made the INCEPTION model an inappropriate choice, as evident from Figure 4.

https://doi.org/10.4314/njt.2026.5954SI

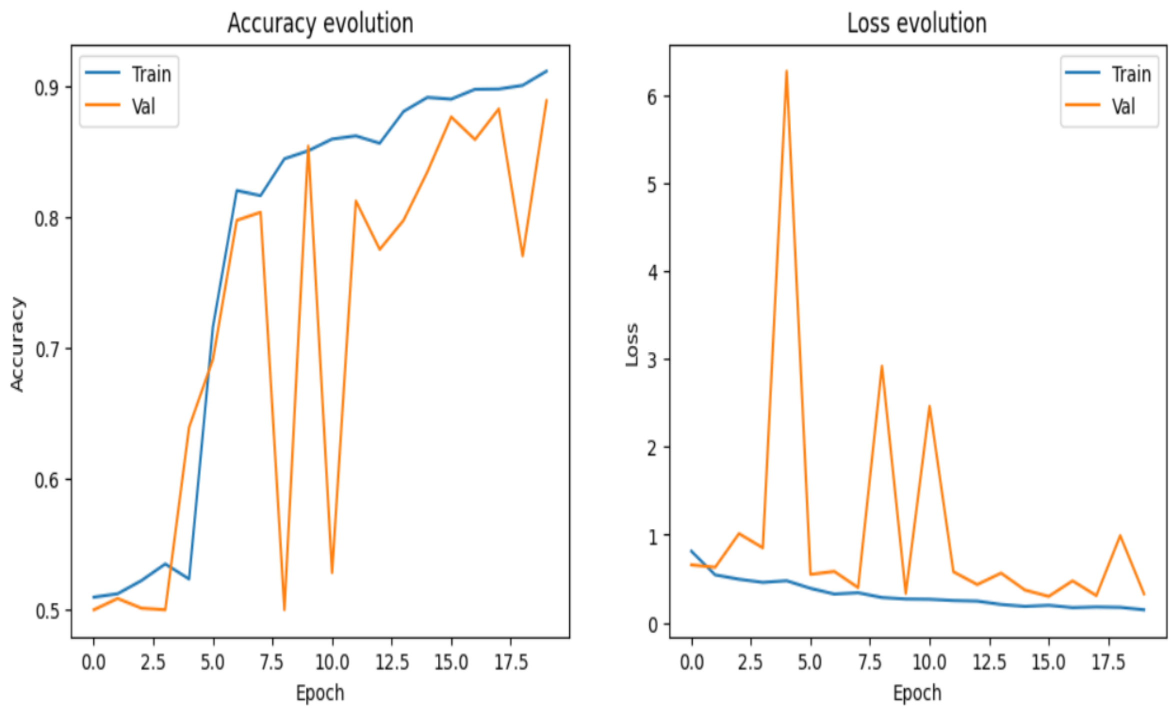

Figure 3: Training accuracy and loss in VGG model

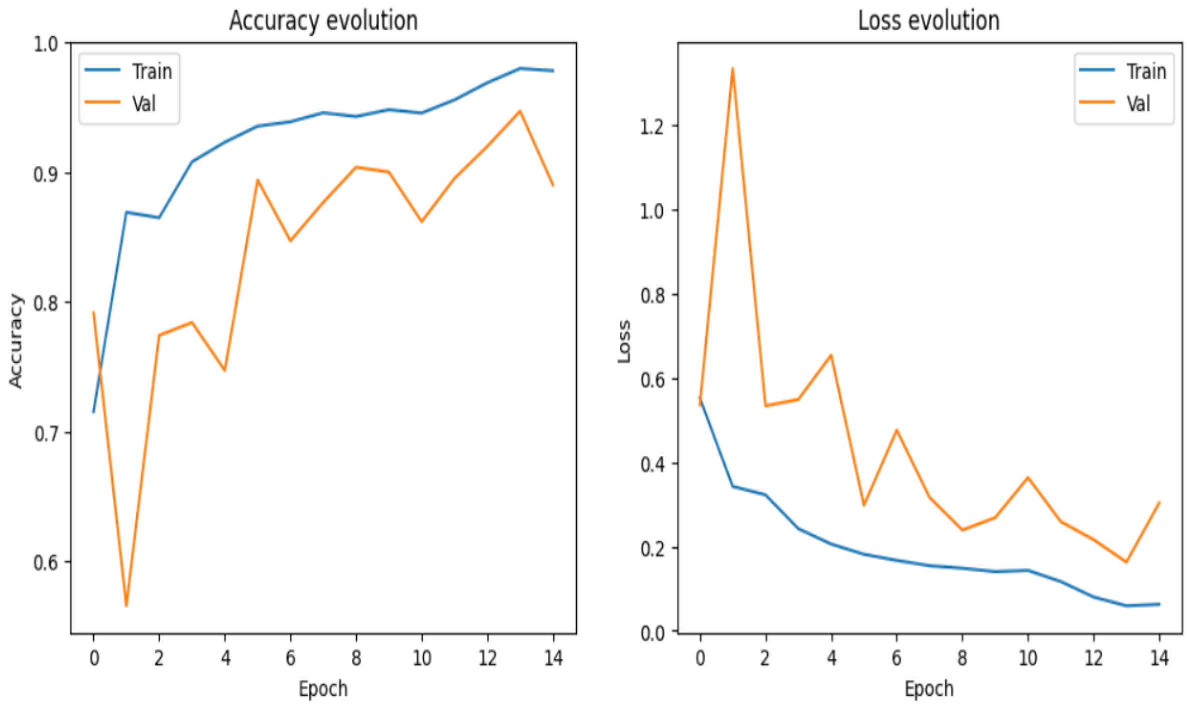

Figure 4: Training Accuracy and Loss in INCEPTION Model

3.3.4 RESNET model

The RESNET model with the characteristic of residual learning because it has 18 layers has a total of 492497 trainable parameters to store a total of 1.88 MB and has predicted values with an accuracy of 87%, a precision of 97%, a recall of 85% and an F1-Score of 90% for the data used [25], taking 15 epochs to train. The accuracy and loss curve after 15 epochs is shown in Figure 5.

https://doi.org/10.4314/njt.2026.5954SI

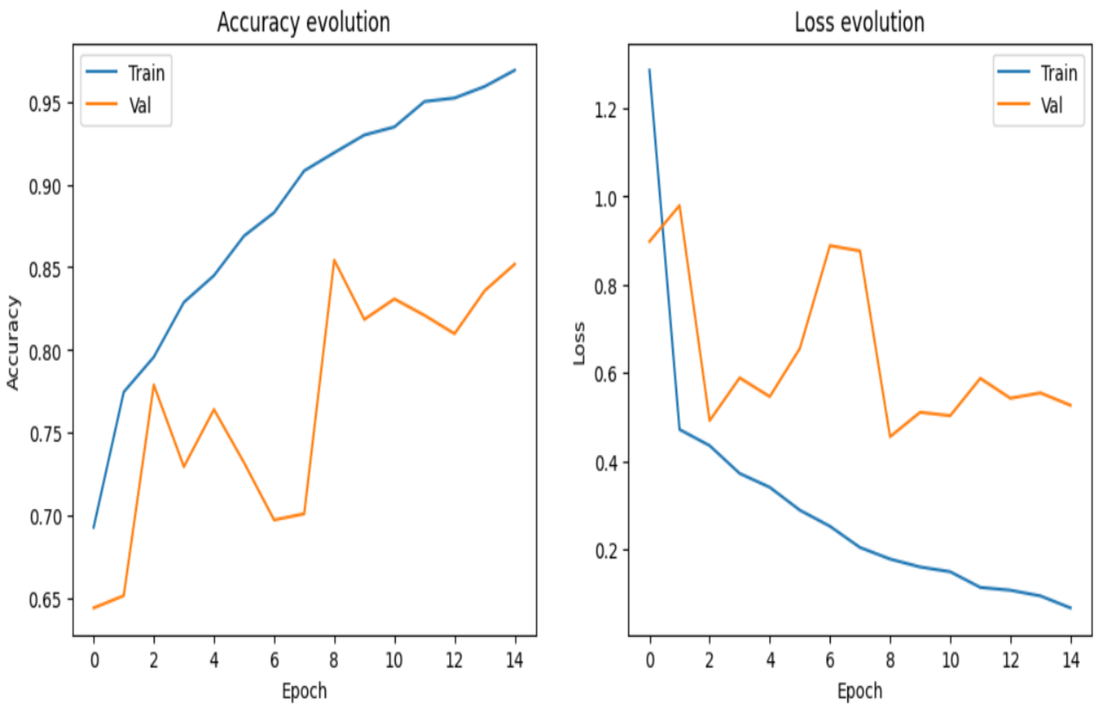

Figure 5: Training accuracy and loss in RESNET model

Prior to use, chest X-ray image preprocessing was performed on each image, including resizing (224 × 224-pixel format) and pixel intensity normalization (to fit EfficientNetB3); options include the following: all images had to go through an augmentation process utilizing various augmentation methods (rotating, flipping, zooming/zooming out, scaling) so that they were mixed with one another and ultimately improved and expanding the potential uses (accuracy)) for all of the training images together. Through these processes listed above, the overall resulting level of robust strength with regard to over fitting decreased significantly for this model and subsequently produced very high classification or prediction accuracies on all testing (unseen); testing (unseen) data (99.6%).

Table 2: Performance outcome of proposed work

Models	**Training epochs**	**Training duration (min)**	**Accuracy**	**Precision**	**Recall**	**F1-Score**
CNN with EfficientNetB3	10	30	99.60	99	97	98
VGG Model	20	11	91	95	91	93
Inception Model	15	5	94	99	91	95
ResNet Model	15	8	87	97	85	90

Using EfficientNetB3 as its base model, the proposed model for use in this application is less prone to over fitting than VGG, ResNet or Inception. This is due to using Transfer Learning and Selective Fine-Tuning to reduce the number of trainable parameters when compared to other networks. Use of data augmentation, Dropout and Batch Normalization were also employed to increase generalization capabilities of the model. Additionally, Efficient Net's Compound Scaling Strategy enables better parameter efficiency for learning distinguishable features of pneumonia with less complexity in the model.

Overall comparative study among all models is represented through Table 2. The proposed model and models that possess higher accuracy during the study are compared with respect to the parameters such as performance metrics that include measures such as training epoch values, time taken to train the models

https://doi.org/10.4314/njt.2026.5954SI

on the dataset, testing accuracy values of models, precision values, recall values, and F1-Score values.

3.5.5 Performance comparison of CNN with EfficientNetB3, VGG model, inception model, RESNET model

This section presents the interpretation of the comparative analysis amongst the different models with respect to the results given by the performance measures such as accuracy, precision, recall and F1 score. Figure 6 depicts the graphical representation among different models like VGG Model, INCEPTION Model, RESNET Model and our proposed CNN Model with EfficientNetB3. The results of these models which are compared include accuracy, precision, recall and F1 score. These are defined on the basis of values presented in the confusion matrix containing the actual class values and the predicted class values of the data [19]. Speaking of accuracy as a metric that deals with accuracy performance, the outcome shows that the 'CNN with EfficientNetB3' model shows the accuracy of 99.60% is the best among all models in predicting pneumonia. The accuracy given out by the INCEPTION model is 94 % which is comparatively less than the accuracy of the proposed model. The VGG model gives out the accuracy of 91% and the RESNET model shows the worst accuracy of 87%. The comparison of the performances of different models with respect to precision is shown through the use of bar graphs in Figure 5. Precision speaks to the measure that illustrates the proportion of images labeled as Pneumonia that are in fact tagged to images with Pneumonia class. The precision metric has been set to 99% by the models CNN with EfficientNetB3 and the INCEPTION model. The VGG and RESNET models possess 95% and 97% precision respectively.

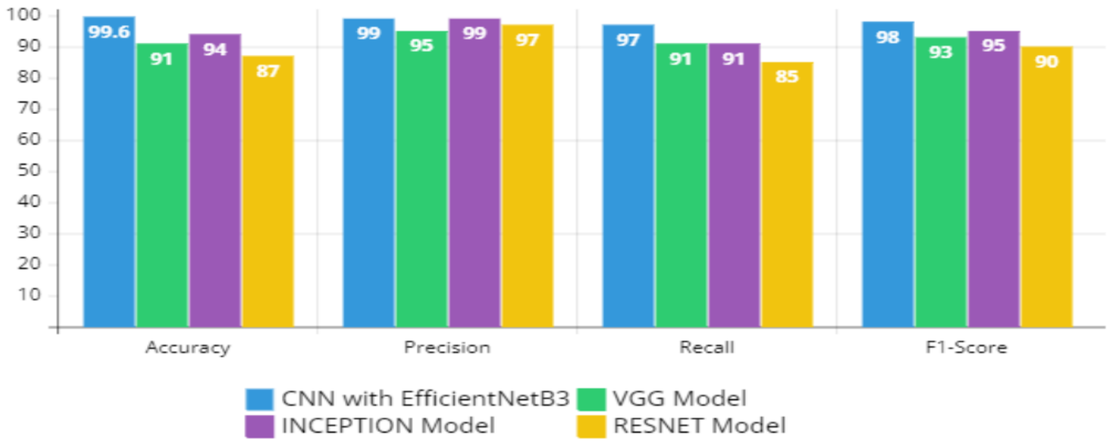

Figure 6: Performance comparison of several models with the proposed model work (CNN with EfficientNetB3)

The recall is the evaluation criterion that computes the correctly distinguished Pneumoniac cases from the entire pneumonia identified in the dataset. A comparative study among the models based on recall is illustrated in Figure 5. The inference made here is that the best performing model with recall 97% is the proposed model CGG with EfficientNetB3 followed by VGG and INCEPTION models with equal recall= 91%, and the RESNET model works until recall= 85%. Hence, the proposed model is declared as the best among the models based on recall. The F1-score is the harmonic mean of precision and recall. The F1-score is defined by combining the values of recall and precision to describe how well the model works. The F1-Score values which are computed to compare the performance of models indicate that the F1-Score value is 98% in the proposed model if we see all models. The values of F1-Score are respectively 95%, 93% and 90% for the models INCEPTION, VGG and RESNET. The CNN Architecture with EfficientNetB3 therefore appears to give the best results in term of the metrics of F1-Score.

3.3.6 Comparison of performance results between the designed model and the original models

The present section of the paper aims to discuss the comparison analysis between the results obtained by CNN with the EfficientNetB3 Model and those obtained by the models displayed in the current state-of-the-art section, shown in Table 3. The current analysis between the current model and existing models displays that the current model performs better compared to other models with 99.60% accuracy. The

https://doi.org/10.4314/njt.2026.5954SI

Precision measure with 99.30% is comparatively higher compared to that of other models. The current recall measure with 97.80% is comparatively good but higher compared to other measures. The F1-Score measure with 98.20% shows that the model performs better and thus more reliable among other current models. In conclusion, the current model 'CNN with EfficientNetB3 Model' performs better compared to other current models displayed in the state-of-the-art section. To improve the balance of image representation in pneumonia vs. non-pneumonia classes, both data augmentation as well as class balanced training were used which expanded the number of representative samples for the minority class (pneumonia) leading to improved training results overall. Stratification of split data into training, validation and test sets also resulted in diversity of class proportions in those sets which helps reduce bias towards the majority class and ultimately improve generalization accuracy for all classes of objects.

Table 3: Performance Comparison between the proposed models and existing models

Reference	Model	Dataset	Accuracy	Precision	Recall	F1-Score
[7]	GoogleNet+ResNet-18+DenseNet-121	Kermany(5,856 images) and RSNA(26,601 images)	86.85%	98.82%	98.80%	98.35%
[8]	VGG16+VGG19	Kermany(5,856 CXR images)	98.55%	98.72%	99.30%	99.01%
[9]	CNN with Filters+SVM+YOLOv3	Publicly Unavailable	99.00%	99.00%	99.00%	99.00%
[11]	CNN+Transfer Learning	Kaggle(5,856 CXR images)	97.00%	97.00%	97.00%	97.40%
[13]	Resnet (Transfer Learning)	Kaggle(5,910 CXR images)	95.00%	96.00%	96.00%	96.00%
[15]	CNN+Transfer Learning	Kaggle(5,856 CXR images)	98.28%	98.00%	97.20%	97.60%
[16]	CNN+INCEPTION v3	Kaggle(7,750 CXR images)	99.29%	98.83%	99.73%	99.28%
Proposed CNN with EfficientNetB3 Architecture		Kaggle (5,863 CXR images)	99.60%	99.30%	97.80%	98.20%

EfficientNetB3 is a CNN architecture that extends the defined limits of traditional transfer learning because it has both (1) an initial set of pertained weights, and (2) a complete fine-tuning of the deeper layers to specifically target the pneumonia-associated features found in chest X-ray images. EfficientNetB3 incorporates its own set of custom CNN layers to create a more feature-refining process, thus providing a greater rate of domain adaptation than traditional approaches to transfer learning, which rely completely on pre-trained fixed feature extractors.

4.0 CONCLUSION AND FUTURE SCOPE

Early detection of pneumonia is crucial for selecting effective treatments and giving timely medication to save lives. The CXR images are commonly used for Pneumonia detection, but due to variability and the efficiency of clinical expertise, accuracy can be affected. To address these challenges, a deep learning model that classifies the radiological images of CXR into normal or Pneumonia classes with excellent accuracy is proposed. The focus is on the specific part of the body initially as the chest and the specific disease of that part as Pneumonia. The studies of existing implementations and proposed models show that the proposed CNN with EfficientNetB3 model provides a significantly high accuracy of 99.6% over the other custom-built models including RESNET-18 (Accuracy: 87%), VGG Net (Accuracy: 91%) and INCEPTION Net (Accuracy: 94%). It is concluded that the CNN with EfficientNetB3 has been found to have the highest accuracy of 99.6% with the Precision, Recall, and F1-Scores as 99%, 97%, and 98% respectively. Being the CNN model integrated with EfficientNetB3 Architecture, it has outperformed the other custom-built models like ResNet-18, VGG, and Inception Net. In future work, this model can be extended to a chatbots where the patients do not have

https://doi.org/10.4314/njt.2026.5954SI

to wait for the doctor's response and can get the results based on their symptoms when asked to the chatbots using advanced deep learning models and natural language processing.

REFERENCES

[1] Adil, M., Royaidar, J., Yassa, R., GonzagaLeong-on, M.,Iqbal, F., Hussain, A., Ali, Q. and Rasheed, A. "Epidemiology and Resistance Pattern in Microbial Pneumonia: A Review: Epidemiology and Resistance Pattern in Microbial Pneumonia." *Pakistan Journal of Health Sciences*, 3(5), pp.27-31, 2022. https://doi.org/10.54393/pjhs.v3i05.229

[2] Pitre, T., Ellen,P., Chaudhuri,D., Saha, R., Rudd, K.,Villar, J., Berry, L. "Corticosteroids for adult patients hospitalised with non-viral community-acquired pneumonia: a systematic review and meta-analysis", *Intensive Care Medicine*, 51(1), pp.917-929, 2025. https://doi.org/10.1007/s00134-025-07912-2

[3] Sable,N., Rathod, V., Deshmukh,J., and Sonavane, S., "Significance of Blockchain Technology in Industrial Applications with an Emphasis on Security Considerations", *In Machine Learning for Environmental Monitoring in Wireless Sensor Networks*, Hershey, PA, USA: *IGI Global*, pp.305-330, 2025. doi: 10.1016/j.rser.2025.116302.

[4] Ahmed, R. "Human Metapneumovirus (HMPV): Epidemiology, Pathophysiology, Clinical Management, and Future Prospects in Treatment and Prevention", *Radinka Journal of Health Science*, 2(3), pp. 312-327, 2025. https://doi.org/10.56778/rjhs.v2i3.417

[5] Andriani, K., and Debi, S., "Semantic Literature Analysis and Deep Learning Algorithm Comparison for Identifying Paru-Paru Diseases from X-rays", *JMATech-Journal of Medical Ai & Technology*, 1(1), pp.7-10, 2026.

[6] Alshanketi, F., Abdulrahman, A., Mathew, K., Vahid, M., Shams, T.,Rana, N., and Ali, T., "Pneumonia detection from chest x-ray images using deep learning and transfer learning for imbalanced datasets", *Journal of imaging informatics in medicine*, 38(4), pp. 2021-2040, 2025. https://doi.org/10.1007/s10278-024-01334-0

[7] Lestari, D., Anggi, M., Aghnia, T., Ryando, R., and Habibah, D., "Deep Learning for Pneumonia Detection in Chest X-Rays using Different Algorithms and Transfer Learning Architectures", Public Research Journal of Engineering, Data Technology and Computer Science, 3(1), pp.10-21, 2025. https://doi.org/10.57152/predatecs.v3i1.1553

[8] Shaikh, M., Qasim, A., and Rabeea,J., "AG-FSNet: A hybrid attention and feature selection network with feature contribution scoring for pneumonia segmentation using CXR images", *Biomedical Signal Processing and Control*, 114 (1), pp.109248-109285, 2026. https://doi.org/10.1016/j.bspc.2025.109248

[9] Sadiq, B., "Maximizing network capacity, control and management in designing a Telemedicine network: a review and recent challenges", *Nigerian Journal of Technology*, 43(1), pp. 80-100, 2024.

[10] Rathod, V., Shyamrao, V., and Himadri, M., "The Role of Congestion-Adaptive Routing Protocol in Mobile Ad Hoc Networks." *The Scientific World Journal*, 1(1), pp. 6296169, 2025. https://doi.org/10.1155/tswj/6296169

[11] Waisi, N., "Comparative Evaluation of Resnet-50 and Efficientnet-B1 for Pneumonia Detection in Chest X-Ray Images Using Transfer Learning", *International Journal of Computational & Electronic Aspects in Engineering*, 6(2), 2025. https://doi.org/10.26706/ijceae.6.2.20250405

[12] Rathod, V., Gumaste,V., Guttula, R., Zade, S., and Singh, R., "Optimization of energy consumption in mobile ad-hoc networks with a swarm intelligence-based ABC algorithm", *Discover Applied Sciences*, 8, pp. 805, 2025. https://doi.org/10.1007/s42452-025-07472-6

[13] Khojare, S., and Bhattacharjee, S., "Pneumonia Identification based on Transfer Learning over Chest X-Ray Images", *In 2025 International Conference on Emerging Trends in Industry 4.0 Technologies (ICETI4T)*, *IEEE*, pp. 1-6, 2025. doi: 10.1109/ICETI4T63625.2025.11132185

[14] Kumar, P.,Verma, S., Shubhanshi, R., Yadav, J., and Sing, S., "Quantitative Analysis of Lung Opacities on Routine Chest X-Ray Radiograph", *International Journal of Scientific Research and Technology*, 3(1), pp.144-151, 2026. https://doi.org/10.5281/zenodo.18220096

[15] Rabbah,J., Mohammed, R., and Larbi, H., "Improving pneumonia diagnosis with high-accuracy CNN-Based Chest X-ray image classification and integrated gradient", *Biomedical Signal Processing and Control*, 101(1), pp.107239, 2025. https://doi.org/10.1016/j.bspc.2024.107239

[16] Abdalla, K., Fatemeh, D., Eghbal, H., and Mourad, O., "HyOCNN: Hybrid-optimized convolutional neural network for robust image classification", *Biomedical Signal Processing and Control*, 113 (1), pp.109040, 2026. https://doi.org/10.1016/j.bspc.2025.109040

[17] Widhiyanti, E., Guruh, F., Aisyah, N., Talitha, O., and Edi, J., "Comparative Analysis of CNN and Fine-Tuned InceptionV3 with and Without Transposition Layer for Chest X-ray Image Pneumonia Detection, " *In 2025 International Seminar on Application for Technology of Information and Communication (iSemantic), IEEE*, pp. 127-132, 2025. doi: 10.1109/ISemantic67418.2025.11291892

[18] Waisi, N., "Comparative Evaluation of Resnet-50 and Efficientnet-B1 for Pneumonia Detection in Chest X-Ray Images Using Transfer Learning", International Journal of Computational & Electronic Aspects in Engineering (IJCEAE), 6(2), pp.89-97, 2025. https://doi.org/10.26706/ijceae.6.2.20250405

[19] Dataset: P. Mooney, “Chest X-Ray Images (Pneumonia),” *Kaggle*, 5,863 images, 2 categories, 2018. [Online]. Available: https://www.kaggle.com/datasets/paultimothymooney/chest-xray-pneumonia