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Romesaa Al-Quraan
Jordan University of Science and Technology

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RESEARCH ARTICLE

Pneumonia Detection Using enhanced CNN Model on Chest X-Ray Images

Shadi A. Aljawarneh*[1], Romesaa Al-Quraan*[1]

[1]CIS, CIT, Jordan University of Science and Technology, Irbid, Jordan

*saaljawarneh@just.edu.jo or rmalqaran20@cit.just.edu.jo

ABSTRACT

Objective: Pneumonia, caused by microorganisms, is a severely contagious disease that damages one or both the lungs of the patients. Early detection and treatment are typically favoured to recover infected patients since untreated pneumonia can lead to major complications in the older (>65 years) and children (<5 years). The objectives of this work are to develop several models to evaluate X-ray Images (XRIs) of the chest, determine whether the images show/ do not show signs of pneumonia and compare the models based on their accuracy, precision, recall, loss, and ROC AUC scores.

Methods: CNN, VGG-19, ResNet-50, and ResNet-50 with fine-tuning are some of the deep learning algorithms employed in this study. By training the transfer learning model and upgraded CNN model using a dataset, these techniques are used to identify pneumonia. The data set for the study was obtained from Kaggle. This dataset included 5,863 chest XRIs, which were categorised into 3 different folders (i.e., train, val, test).

Results: According to the experimental findings, the ResNet50 model showed the lowest accuracy, i.e., 82.8%; while the upgraded CNN model showed the highest accuracy of 92.4%. Owing to its high accuracy, CNN was regarded as the best model in this study. The techniques developed in this study outperformed the popular ensemble techniques, and the models showed better results than those generated by cutting-edge methods. Deep learning models can detect the progression of pneumonia, which improves the general diagnostic accuracy and gives patients new hope for speedy treatment.

Conclusions: Since enhanced CNN and ResNet50 showed the highest accuracy compared to other algorithms, it was concluded that these techniques could be effectively used to identify pneumonia after performing fine-tuning. It should be noted that the improved CNN would be more helpful in diagnosing pneumonia than the conventional method, which involves the healthcare provider reviewing the patient's medical history, performing a physical exam, and ordering diagnostic procedures like a chest X-ray. This information helps in identifying the form of pneumonia affecting the patient. Furthermore, pneumonia can take a severe turn and become fatal.

1. Introduction:

To keep the body healthy, the lung—the centre of the respiratory system—offers oxygen to the body, while eliminating carbon dioxide[1]. However, the body could be exposed to several factors that damage lung health and cause diseases, with pneumonia being one of the most hazardous. Pneumonia, caused by microorganisms, is a severely contagious disease that damages one or both the lungs of the patients[23]. Early detection and treatment are typically favoured to recover infected patients since untreated pneumonia can lead to major complications in the older (>65 years) and children (<5 years)[3] Every year, the disease claims the lives of 700,000 kids and affects 7% of the global population[4]. The World Health Organisation (WHO) states that there are many degrees of pneumonia, from mild to severe, extremely risky, and potentially fatal. Early detection and effective treatment are therefore often preferred to help infected patients recover [3]. There are 4 distinct forms of pneumonia: 1) Community-Acquired Pneumonia (CAP) - pneumonia contracted in a community environment, outside the hospital [5] ; 2) Hospital-Acquired Pneumonia (HAP) - pneumonia that was contracted ≥48 h after being admitted to an inpatient facility, such as a hospital; 3) Ventilator-Associated Pneumonia (VAP) [6] – this form of pneumonia is noted in patients who were mechanically ventilated using a ventilator for ≥48 h. 30% of the VAP cases take place in the Intensive Care Units (ICUs) [7] ;4) Aspiration pneumonia – arises from the aspirated microbes from the oropharynx or stomach [8].

Viruses, fungi, and bacteria can all cause pneumonia [9] .Respiratory syncytial viruses are the most common cause of CAP in children under the age of five. Additionally, *Streptococcus pneumonia* affects people of all ages [10] . The following are the most classic symptoms of pneumonia: Dyspnoea, cough, fatigue, and depression, which are all morbidity-related conditions that can be challenging to manage. Management of symptoms is made considerably more challenging by the psychological strain that comes with having a chronic lung disease, like pneumonia, which can be life-threatening [11] .Studies have shown that neuraminidase inhibitors can lessen viral pneumonia transmission upon exposure and improve a patient's clinical development in ICUs. Ribavirin has been used to treat children and immunocompromised people with syncytial respiratory viruses [12] .Other steps like proper nutrition, immunisation, and favourable environmental factors also help in preventing pneumonia [9].

Owing to the significant advancements in the field of deep learning, the medical diagnostic processes have become revolutionised and are more accurate, accessible, and automated for identifying and analysing images, which has significantly improved their performance [13]. Furthermore, thanks to the power of cloud computing, smart models may be used on a large scale and are faster than people. Thus, artificial intelligence techniques help in comparing and grouping patients with different types of pneumonia [14].

Before the development of image processing and deep learning processes, only highly skilled radiologists could diagnose and treat pneumonia. Now, diseases can be detected more automatically. To diagnose pneumonia with the least amount of time, effort, high accuracy, and higher probability of successful treatment, the researchers and designers hastened to develop multiple systems, artificial models, and numerous computer-aided detection methods [15] .Even though several studies have achieved a rather good model accuracy, the magnitude of the dataset raises the possibility of overfitting. To establish a strong and trustworthy model for the early diagnosis of pneumonia that can save lives, more efforts and research needs to be conducted [16] [17] [18] [19].

In this study, a variety of pneumonia detection models have been presented which were based on a massive dataset of XRIs, using an improved Convolutional Neural Network (CNN) model and transfer learning methods, such as VGG19, ResNet, and Fine-tune ResNet model. Additionally, some of the research questions addressed in this study were as follows: (1) Which model was more accurate at detecting pneumonia? (2) Can the enhanced CNN model outperform the transfer learning models?

To generate a model with four layers and varying numbers of filters for every layer, the first model will use a CNN, whilst the second model will use a deep neural network called the Residual Network50V2. A Visual Geometry Group net (VGG19) will be used to generate the third model, and the fine-tune Residual Network-50 model will be used to create the final model. The information used in this investigation came from Kaggle.

"Chest X-Ray Images (Pneumonia)" was the dataset used in this study. This dataset, which includes 5,863 images, comprises XRI chest images that can be used to identify the type of pneumonia. The images retrieved from the dataset were subjected to several pre-processing techniques, such as cropping and resizing. Then, the data was used to train the previously mentioned models. The ResNet50 showed a low accuracy of 82%, VGG-19 showed an 88% accuracy, while the fine-tune Residual Network-50 model showed the best accuracy of 91.8%. Additionally, the enhanced CNN showed the highest accuracy, i.e., 92.46%, compared to the other transfer learning models implemented in this study. This result indicated that the enhanced CNN technique could outperform the other transfer learning models. This could be attributed to the fact that pre-trained models were trained using natural images; whereas the enhanced CNN model was trained using medical images.

Section 1 below has presented a summary of all related studies, while Section 2 presents the study framework that describes how the researchers would fulfil their study objectives, right from the data loading step to the result step. Section 3 presents an outline of the techniques, materials, dataset features and augmentation techniques used in the study. All experiments used in the study have been described in Section 4, while the discussions have been presented in Section 5.

2. Related works:

Deep-Learning (DL) is extensively adopted in image processing for the identification, classification, and detection of XRIs. It can also be used to identify pneumonia. The following are a few studies that were reviewed for the diagnosis or classification of pneumonia:

A DL system was developed for identifying pneumonia [3] .The researchers used carried out a binary classification using the SoftMax classifier to assess the effectiveness of the DL scheme to recognise diseases. The AlexNet was able to identify >98% of the images in the database under consideration. Furthermore, in[20], the researchers studied and compared the effectiveness of various computer-assisted techniques to identify lung diseases, and proposed an updated model that could detect pneumonia, by implementing many Machine Learning (ML) techniques, such as KNN, CheXNet, DENSENET, CNN, RESNET, and ANN. They noted that the CNN model showed a better detection accuracy and could detect many lung diseases.

In [21] ,the researchers proposed a novel DL model to diagnose pneumonia disease using Chest X-ray images. Some of these models included SqueezeNet, VGG19, AlexNet, VGG16, and Inception-V3. Additionally, they used many ML classifiers like KNN, ANN, NB, LR, SVM, and AB. Their results showed that the Inception-V3 transfer learning technique and the ANN showed a better performance and achieved a high classification accuracy of 97.19%. In [22] ,the effectiveness of single and ensemble learning models for the classification of pneumonia was examined. Most of the ensembles used were fine-tuned variations of (ResNet50, InceptionResNet V2, and MobileNet V2). The InceptionResNet V2 model showed 93.52% of the F1 score for one model. Additionally, compared to other ensembles, a 3-model ensemble (ResNet50 with MobileNet V2 and InceptionResNet V2) was seen to be more accurate (94.84% of F1 score).

In [23] ,the researchers compared the current deep CNN architecture for automatically binary classifying images of pneumonia based on fine-tuned models of (VGG16, Inception ResNet V2, DenseNet201, VGG19, Inception V3, MobileNet V2, Resnet50, and Xception) and retraining a baseline CNN. The findings revealed that Resnet50's fine-tuned model showed a satisfactory level of performance and better training and testing accuracy (i.e., >96%). In [24] ,the researchers developed a processing methodology that relies on a CNN model and DL techniques. This method showed an accuracy closer to 90%. Using a CNN model based on transfer learning, [25] developed a fine-tuned VGG16 model to identify pneumonia using X-ray images. This technique showed a 93.6% accuracy.

To help doctors operating in rural areas, [26] suggested a DL framework for diagnosing pneumonia from X-ray images. To develop an energy-efficient and bandwidth-preserving technology for far-end pneumonia detection, the X-ray images are captured in the form of Compressed Sensing (CS) measurements, which implies that very few samples are visible. Thus, the simulation shows that even when just 30% of samples are delivered, the proposed technique accurately diagnoses pneumonia with a 96.48% rate.

In [27] ,the researchers illustrated a technique for detecting pneumonia using multilayer perception and CNNs. The results revealed that the CNNs showed a 92.63% accuracy, whereas the multilayer perceptron technique showed a 77.56% accuracy. [28] provided an improved model that relied on transfer learning to detect pneumonia from X-ray images. This technique showed an 80% accuracy. To detect the occurrence of pneumonia, [29] proposed an altered DL strategy using the CNN model and features extracted from chest X-ray images. The findings obtained demonstrated that the proposed CNN technique showed an 89.0% accuracy.

3. Methods and materials:

3.1. Study architecture:

As described in Figure 1, the technique used in this study can be categorised into 3 subsections, where Section 1 included loading and visualising the dataset. In subsection 2, the researchers used the data pre-processing steps for imaging the data and preparing it for the DL model. Thereafter, they trained the enhanced CNN model in addition to 2 transfer learning models (ResNet50, VGG Net19). They further fine-tuned the ResNet50 for improving its performance. This included training the top layer weights in the pre-trained model, combined with the added classifier.

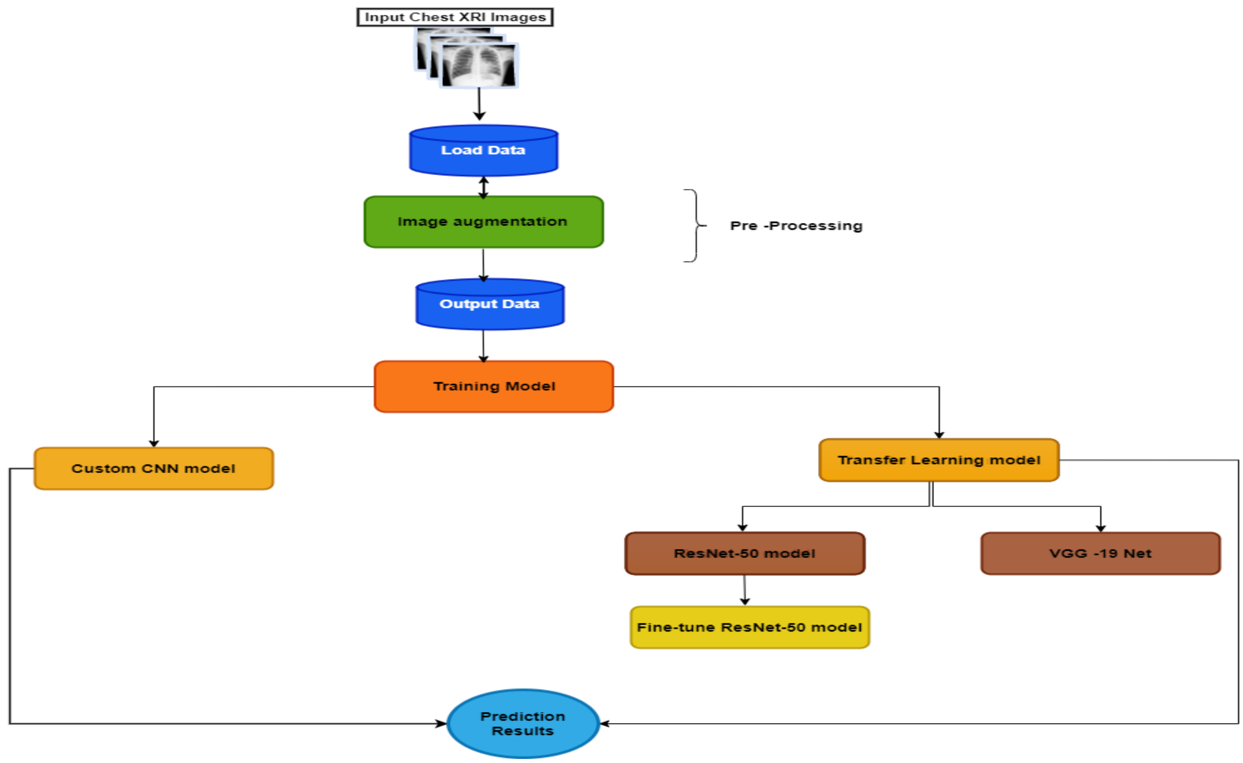
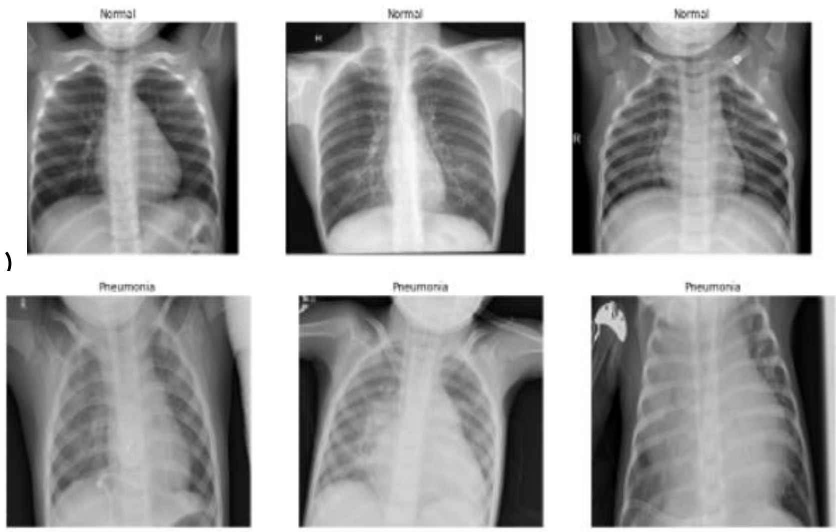


Figure 1: *Flow diagram of the Study Architecture*

3.1.1. Data characteristics:

All data used in this report was acquired using the Kaggle dataset, which was the biggest data science community in the world. Users can look for and post datasets that the DL community can use to interpret data and address a variety of issues. This dataset is called Chest X-Ray Images (Pneumonia). From retrospective cohorts of paediatric patients at the Guangzhou Women and Children's Medical Centre, aged one to five, anterior-posterior chest X-ray images were selected. The patients underwent chest X-ray imaging as part of their routine medical care. The researchers performed a quality control check on the chest radiographs before evaluating them, eliminating any that were blurry or illegible. The diagnosis for the images was then evaluated by two specialists before being authorised for inclusion in the AI system. To ensure that there were no grading issues, a third expert reviewed the evaluation set. The dataset comprised 5,863 chest XRIs, as described in Figure 2. This dataset includes 3 folders of chest XRIs; Folder 1, i.e., "Train," contains 5,216 images (PNEUMONIA=3875, NORMAL=1341), Folder 2, i.e., "Val," contains 624 images (PNEUMONIA=390, NORMAL=234), and Folder 3, i.e., "Test," contains 16 images (PNEUMONIA=8, NORMAL=8) that are unlabelled chest XRI for testing.



(1)

(2)

Figure 2: *(1) Chest XRIs without pneumonia, (2) Chest XRIs with pneumonia*

Figure 3 presents the ratio distribution in the dataset that can be characterised by many categories (normal, pneumonia) in every data set, highlighting the imbalance in the dataset.

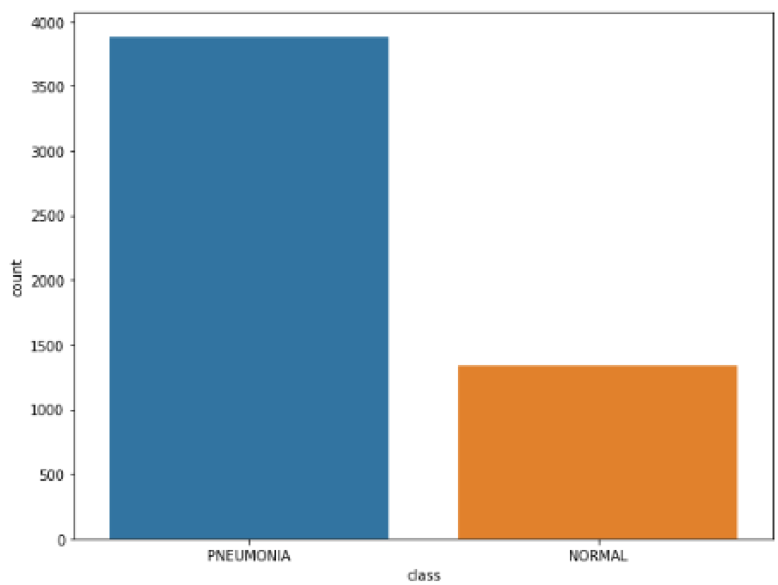


Figure 3: *Histogram depicting the ratio distribution*

3.1.1.1. Data pre-processing:

3.1.1.2. Data Augmentation:

The "data augmentation" technique involves artificially boosting the volume and complexity of the already-existing data [30] .This technique can be used to maximise the data for fine-tuning the parameters, limit the distance between the training and validation set, and decrease the validation error, which permits decreasing the training error [30] .

Though the dataset used in this study, which included 5,863 images, was effective, the researchers increased the no. of images with a technique called data augmentation since most CNN models require a substantial amount of data to be trained to optimise the parameters. Data augmentation was implemented using a variety of strategies, including:

1. **Shift range:** This form of data augmentation is implemented to specify the slant angle in degrees. Here, the image was sheared by 20% using the shear range=0.2.
2. **Flipping:** In this form of data augmentation, the primary image is flipped both vertically and horizontally to create new images. The properties of the image are preserved but the

pixels are rearranged when the image is flipped [31] . The vertical and horizontal flips are supposed to have values that are either true or false. Here, the horizontal values were accurate whereas the vertical values were seen to be false.

3. **Rescale:** This data augmentation involves scaling the primary image from one range to a different range to produce new images. The rescaled value in this study is 1. /255, which is used to change the range of pixels from [0,255] to [0,1].

These augmentation techniques were selected as they are popular and produce the best outcomes.

3.2.1. Enhanced Convolutional Neural Network (CNN) model:

The CNN is a form of neural network that uses DL processes to function, and it is a very popular design used to manage numerous ML and DL-based tasks [35]. It has proven to be more adept at a variety of tasks, including picture categorisation, object identification, and medical image analysis [32 33] .The fundamental tenet of CNN is that it takes local characteristics out of high-layer inputs and transmits them to lower layers for additional intricate features [33].

After pre-processing the images in this study, the researchers suggested a simple CNN model. This model has seven layers, the first four of which have a filter size of 3×3. They chose this specific filter size because it allows for weight sharing, decreases the computational costs, and helps in detecting the image corners in the best possible manner [34].

The convolutional layer had (32, 64, 128, and 256) filters in each of the first four layers. Additionally, because the Relu function does not stimulate all the neurons at once, it was used as an activation function for convolutional layers. The model then employs a max-pooling layer with a 2×2 filter to obtain the maximum summary of the input image and to decrease the dimensionality of the image by reducing the no. of pixels in the output of the previous convolutional layer. In layer 5, the researchers this function to the flatten layer for converting the resulting 2D arrays from the pooled feature maps into one long continuous linear vector.

In Layer 6, the dense layer with the Relu activation faction was employed. The final layer is a fully linked dense layer with 128 neurons and a sigmoid output layer, which classifies the outcomes and determines whether the input XRI contains pneumonia using the sigmoid function. The proposed (improved) CNN model architecture is shown in Figure 4.

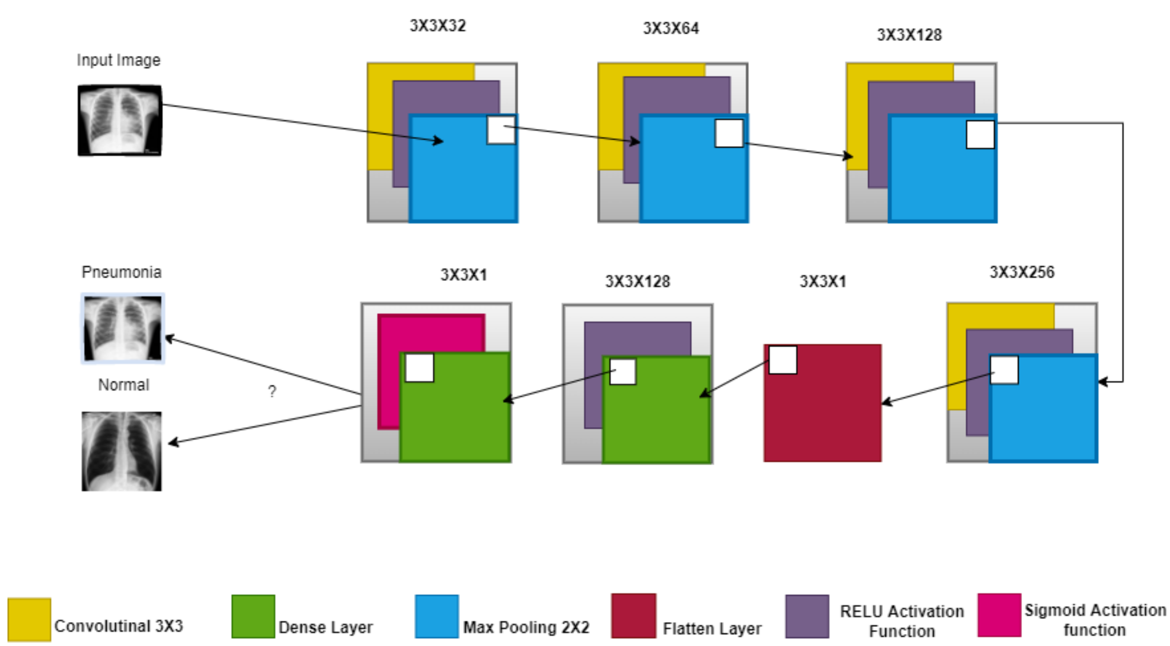


Figure 4: *Enhanced CNN model architecture*

3.2.2. Transfer learning model:

Instead of building an improved CNN model specifically for the image classification job, transfer learning is used as a DL strategy that reuses a pre-trained CNN model, which was pre-trained on a large dataset, like the ImageNet.

3.2.2.1. ResNet-50:

Microsoft released the ResNet-50 CNN model in 2015 to facilitate deep CNN training, ushering in ongoing developments in deep neural networks [35] .It has 26 million parameters and 50 layers. The features are deduced from the residuals, which result from subtracting the features obtained from the inputs in the layer [36] .The ResNet permits the direct connection of input layers (x) to a different layer (n+x), allowing for the stacking of additional layers and the formation of deep networks [36] . Using the ResNet50 CNN model to categorise and identify pneumonia in XRIs, the researchers have proposed a precise and comprehensive computational pneumonia diagnosis framework in this study. To enhance and get better results, they have also fine-tuned the ResNet Model.

3.2.2.2. VGGNet-19 model:

A promising DL architecture called VGG-Net 19 is used for identifying and extracting the information from ocular images[37] .In 2015, Zisserman and Simonyan constructed the VGG Net CNN model for the ILSVRC-2014 contest, where they came in second [38]. Because it employed filters with a size of 3×3, the VGG-Net model is referred to as a simple CNN model [38] .It has 19 convolutional layers, with an input size of 224 × 224 pixels, and is made up of 13 convolutional and 3 fully linked layers [39]. Here, the researchers classified and identified pneumonia in XRIs using a pre-trained VGG-19 CNN model.

3.3. Model Evaluation Metrics.

Table 3 presents the confusion matrix that was the standard for assessing the DL model performance. Using this confusion matrix, 3 measures were used for evaluating all models, as denoted in Table 2.

Table 2: confusion matrix measures to evaluate the models

Measures	Equations
Accuracy	(TP+TN)/(TP+FP+TN+FN).
Precision	(TP/ (TP+FP))
Recall	(TP/(TP+FN)).

Table 3: TP: True positive, TN: True Negative, FP: False Positive, FN: False Negative.

	Actual positive (pneumonia) TP	Actual negative (Normal) FP
Predicted positive (pneumonia)	TP	FP
Predicted negative (Normal)	FN	TN

When the model accurately predicts the positive class (**pneumonia**), the result is deemed to be a True Positive (TP). False-Positive (FP) outcomes occur when the model forecasts the positive class wrongly (**pneumonia**). When the model accurately predicts a negative class (**Normal**), the result is a True Negative (TN). False-Negative (FN) is a result where the model predicts the negative class erroneously (**Normal**).

4. Results:

The authors respond to the research questions, previously outlined based on these findings. According to Table 1, the ResNet50 model had the lowest accuracy at 82.8%, while the enhanced CNN model displayed the highest accuracy of 92.46%. Additionally, the ResNet50 with Fine Tune showed a 91% accuracy, surpassing the VGG Net19 and ResNet50 without Fine Tune transfer learning models, and the model's accuracy value is nearly identical to that of the CNN model.

Figures 6-9 show, respectively, the accuracy and loss graph from the testing and validation phases of the recommended CNN, VGG-19, ResNet-50, and ResNet-50 fine-tuning models. Because of their high accuracy, the CNN and Resnet50 fine-tuning models were regarded as the best models. The results indicated that the enhanced CNN and the Transfer learning models can compete with one another. However, during training, epochs were 35 and batch sizes were 32. An early halting mechanism was put in place to prevent overfitting. An early halting mechanism is used when the model loses its ability to learn and tends to overfit. The test set was used to evaluate the model, and the results are given in Figures 6-9, which demonstrate how the system learns despite having 35 epochs as indicated in Table 2. The CNN, VGG-19, ResNet-50, and Fine-Tuning ResNet-50 models demonstrate that the system, during the testing and validation phase, has ceased to function at EPOC 17.5, 25.5, 10, and 14.5 correspondingly, indicating that the system has stopped learning at those points in the epoch. The early stopping strategy will thereby improve the generalisation of pneumonia prediction in deep neural networks, enhancing the performance and accuracy of the predictive system.

Table 4: Experiment Results for the proposed CNN, VGG-19, ResNet-50, and ResNet-50 fine-tuned model

Model	Epoch	Steps/Epoch	Accuracy	ROC AUC	Recall	Precision	Loss
CNN	30	35	92.4%	95%	96%	90%	0.25%
VGG Net19	30	35	87.3%	94.9%	94%	87.7%	0.28%
ResNet50	30	35	82.8%	93.5%	80.6%	80.6%	0.40%
ResNet50(Fine tune)	30	35	91%	97%	88%	88%	0.27%

Figure 5 shows that ResNet displays the lowest accuracy and CNN has the highest accuracy. However, applying the Fine-tune mechanism for making significant improvements, helped in increasing the accuracy rate of ResNet, similar to CNN.

Figure 10 displays confusion matrices that summarise the accuracy and types of mistakes that the three different detection models (CNN, VGG-19, and ResNet-50 Fine-Tuning ResNet) are making in determining whether the XRIs are pneumonia-related or not. The model's confusion matrix helps to assess the models' reliability in terms of their ability to minimise medical costs. The researchers used three metrics in Table 2 to assess the models' performance.

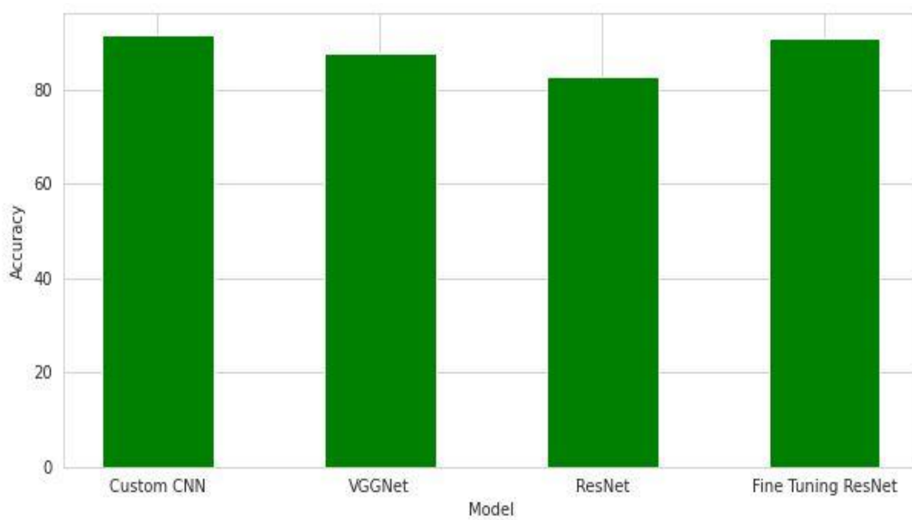


Figure 5: *Histogram distributions of the Accuracy values displayed by the CNN, VGG-19, ResNet-50 and the Fine-Tuned ResNet models*

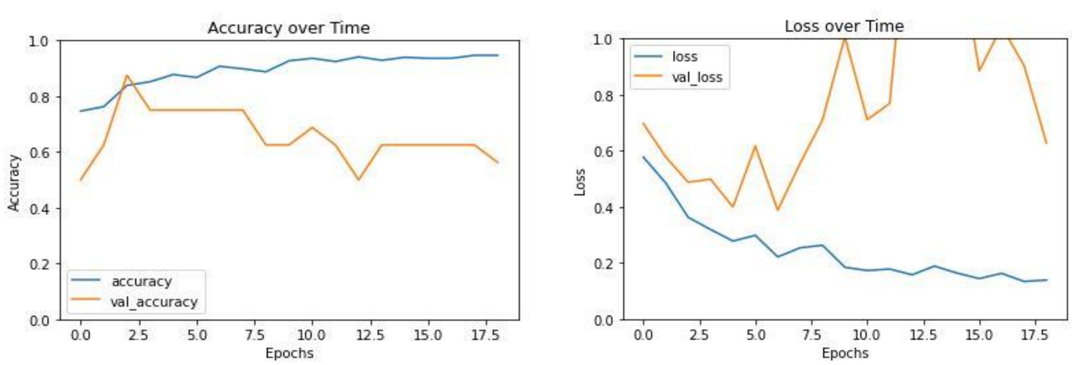


Figure 6: *Accuracy and loss graph of the testing and validation phase for proposed CNN*

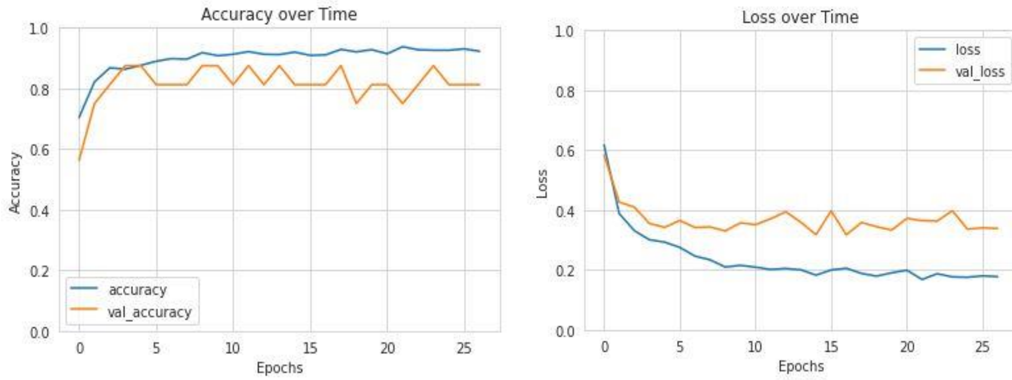


***Figure 7:** Accuracy and loss graph of the testing and validation phase for VGG-19*

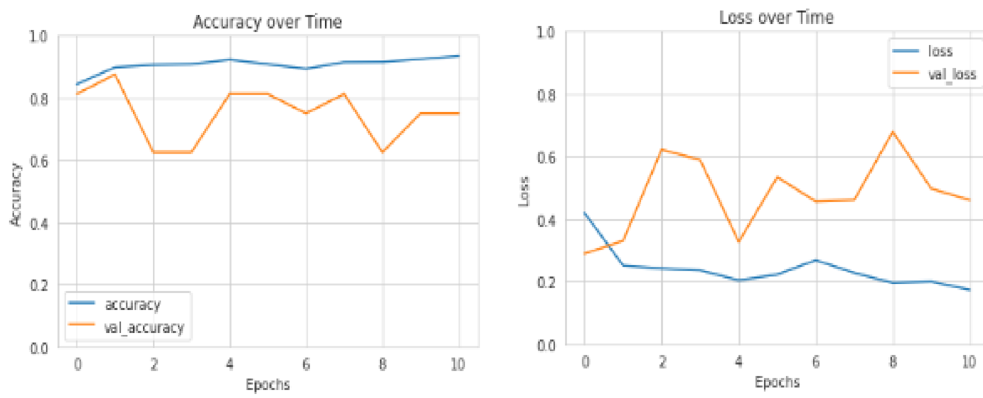


***Figure 8:** Accuracy and loss graph of the testing and validation phase for ResNet-50.*

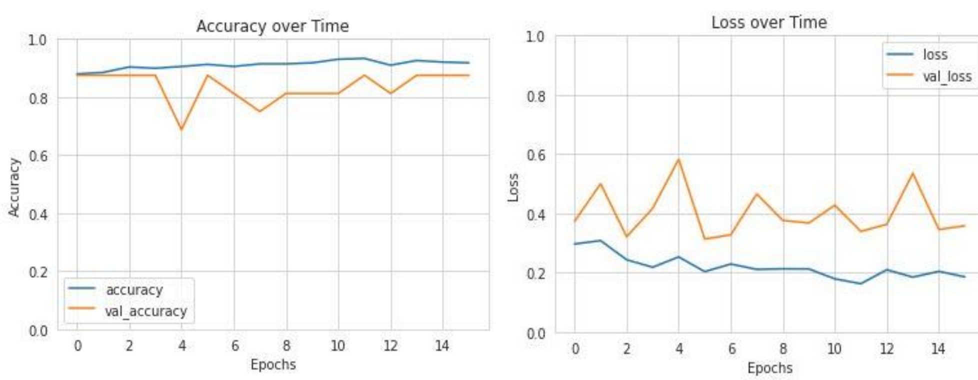
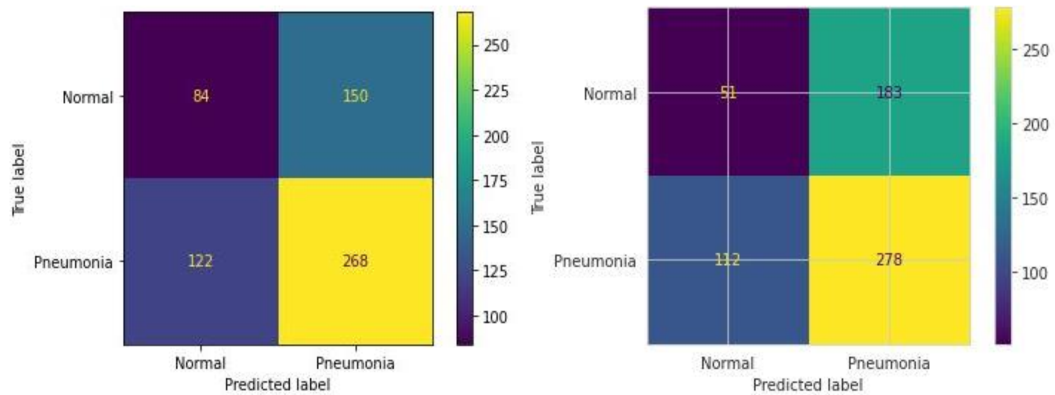


***Figure 9:** Accuracy and loss graph of the testing and validation phase for Fine-Tuned ResNet-50.*



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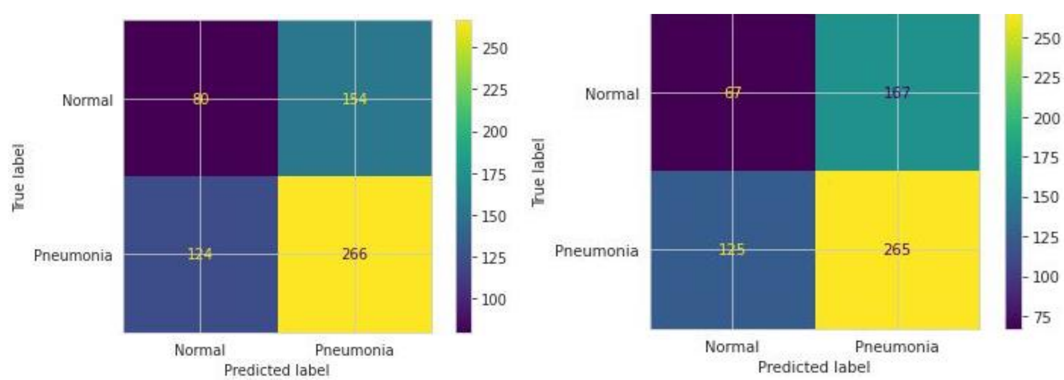

(4)

Figure 10: *Confusion Matrix for: (1) CNN, (2) ResNet-50, (3) VGG19, (4) ResNet-50 _fine tune*

5. Discussions

After reviewing the literature, the researchers noted that most of the studies related to DL, employed transfer learning without enhanced CNN, although the opposite is also true. They also discovered that most studies have inaccurate results since they use a small dataset for training their models. Although CNN has shown good performance in many fields, it can still outperform transfer learning models. As a result, in this study, the researchers intended to compare how the transfer learning and enhanced CNN models could be used to identify pneumonia from a collection of chest XRIs. Numerous academics have suggested that additional research be conducted utilising methodologies including, conducting tests using various pre-processing settings, CNN, and data augmentation processes [24], before designing a high-accuracy detecting model. Table 1 has presented a comparison of the accuracy rate of the proposed technique with the accuracy rates published in the earlier studies that utilised the same chest XRI dataset.

Table 1: *Comparison of the accuracy values published in the earlier studies using the same dataset, with that noted using the proposed approach*

Research #	Study	Year	Methods	Accuracy (%)
R 1	40	2020	CNN MobileNet ResNet-18 ResNet-50 VGG19	91.40% 92.00% 85.00% 87.00% 90.00%
R2	41	2020	CNN model 1 CNN model 2 VGG16 VGG19 ResNet50 Inception-v3	85.26% 92.31% 87.28% 88.46% 77.56% 70.99%
R3	42	2020	ResNet152V2, MobileNetV2, CNN, LSTM.	99.22% 96.48% 92.19% 91.80%
R4	28	2020	CNN Model 1 CNN Model 2 CNN Model 3 CNN Model 4	90.68% 89.32% 79.80% 74.98%
R5	43	2018	deep CNN	84.00%
R6	44	2018	CNN	78.50%
The proposed four models used in this study	-	2022	CNN VGG Net19 ResNet50 ResNet50 (Fine tune)	92.46% 88.62% 82.8% 91%

After comparing the model proposed in this study with those in R1, R2, R4 (Model 1, Model 2, Model 3, Model 4), R5, and R6, it was noted that our model showed a higher accuracy rate than those proposed earlier. The results also indicated that in R1, the researchers used 2 forms of ResNet (ResNet-18, and ResNet-50) models, which displayed accuracy of 85.0%, and 87.0%, respectively, thereby surpassing the value achieved by the ResNet-50 model in this study.
However, in this study, after the researchers fine-tuned this model, the new fine-tune ResNet-50 model showed a higher accuracy rate of 91%. Regarding R2, the results showed that CNN model 1 showed less accurate values (85.26%) than the CNN model used in this study (i.e., 92.46%). However, their CNN model 2 showed similar accuracy rates (92.31%) as our model. The researchers in R2 used 2 VGG variants (i.e., VGG16 and VGG19), which showed accuracy values of 87.28% and 88.46%, respectively. Our VGG 19 surpassed theirs with an accuracy result of 88.62%, though in very insignificant proportions.

Compared to the CNN model (92.19%) used in R3, our CNN model showed a slightly better accuracy rate, i.e., 92.46%. However, their ResNet152V2 model showed a better performance than all the accuracy values displayed in the other studies by showing a perfect accuracy result of 99.22%. In R4, the researchers used 4 CNN models (i.e., CNN Models 1, 2, 3, and 4) which showed accuracy values of 90.68%, 89.32%, 79.80%, and 74.98%, respectively. Thus, it could be concluded that the CNN model used in this study outperformed all the CNN models used in R4. Furthermore, in R5 and 6, the researchers used CNN models that displayed an accuracy of 84.00%, and 78.50% respectively, which was significantly lower than the value displayed by our CNN model. Additionally, the results of the literature survey indicated that the researchers in R1 used the MobileNet model that showed a 92.0% accuracy, which surpassed the accuracy value displayed by Inception-v3 (70.99%) in R2. However, the MobileNetV2 model used in R3 displayed an ideal accuracy rate of 99.22%, outperforming the MobileNet model used in R1. Thus, based on the above assessment, it could be concluded that the models used in this study showed a similar performance to the earlier models. This study has various drawbacks, including a shortage of data, since a sizable dataset is needed to obtain the best results, which required the researchers to create new images using the existing ones.

Additionally, there are limitations on the resources that can be used to train models, such as computer and memory issues. These drawbacks can influence the ability of the model to yield accurate results, hence to deliver more accurate detection and classification models in the future, larger datasets and high-quality computers are needed to overcome these constraints.

Because the enhanced CNN and ResNet50 showed the highest accuracy compared to other algorithms, it was concluded that these techniques could be effectively used to identify pneumonia after performing fine-tuning. It should be noted that the improved CNN would be more helpful in diagnosing pneumonia than the conventional method, which involves the healthcare provider reviewing the patient's medical history, performing a physical exam, and ordering diagnostic procedures like a chest X-ray. This information helps in identifying the form of pneumonia affecting the patient. Furthermore, pneumonia can take a severe turn and become fatal.

6. Conclusions:

Pneumonia, caused by microorganisms, is a severely contagious disease that damages one or both the lungs of the patients. Early detection and treatment are typically favoured to recover infected patients since untreated pneumonia can lead to major complications in the older (>65 years) and children (<5 years). Every year, the disease claims the lives of 700,000 kids and affects 7% of the worldwide population. Early detection and treatments are therefore often preferred to help infected people recover. With the use of an improved CNN model and transfer learning models like ResNet, VGG19, and Fine-tune ResNet model, numerous pneumonia detection models will be assessed in this study using a vast data set of XRIs. After pre-processing the images, these models were applied to the XRI chest dataset. According to the results, the ResNet50 model had the lowest accuracy at 82.8% and the enhanced CNN model had the best accuracy at 92.46%.

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