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Report On

Pneumonia Classification on TPU

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Abstract

Pneumonia is an infectious lung illness that is one of the leading causes of mortality in children under the age of five. One of the most common methods for detecting pneumonia is using chest X-ray images. Several Machine Learning algorithms have proven effective in providing computer-aided diagnosis by automatically classifying medical images. In the realm of medical research, deep learning applications have extended their scope. In this paper, a model that automatically selects the best parameters and two models using transfer learning has been proposed which classifies chest X-ray images as depicting pneumonia and normal. The proposed models uses the pre-trained weights for transfer learning models and kerastuner for the other CNN model. We utilized four well-known performance metrics to conduct comparisons with other state-of-the-art models, yielding the results where fine tuned Efficient Net model achieved remarkable performance with 98and F1 score of 0.98 followed by accuracy of 92CNN - keras tuner model respectively. These positive results allows to consider this research and proposal as alternative to be used in detecting the disease where there is lack of equipment and resources..

1 Introduction

Pneumonia is a very common disease caused by a variety of microbial species, including bacteria, viruses, and fungi. The word ”pneumonia” comes from the Greek word ”pneumon”, which is transcribed in the lungs. Therefore, the word pneumonia is associated with lung disease. In clinical terms, pneumonia is an infection that probably causes deterioration of the parenchyma of one or both lungs(Gupta et al. (2008)). WHO characterized pneumonia, a type of severe lung disease affecting the lung parenchyma and oxygen. Conclusions depend on the clinical appearance, armed with chest X-rays, which reveal some novel shadows. Different types of pneumonia require unique administration techniques to respond to different microorganisms and different patient factors(Bartolf and Cosgrove (2016)).

It is the leading cause of death in children under the age of five worldwide (about 12.8 percent of annual deaths). It's also a prominent source of illness and mortality in adults all across the world, especially in China. Pneumonia is Japan's third largest cause of death, with a greater mortality rate among the elderly, particularly those over the age of 80(Asnaoui et al. (2020)). The World Health Organization (WHO) has created a set of guidelines for diagnosing pneumonia. Several investigations investigating the integrity of these recommendations, on the other hand, have found that low specificity is overshadowing strong sensitivity(Naydenova et al. (2016)).

The difficulty in making a therapeutic choice in the treatment of pneumonia is due to the inability to identify the infectious organism. Antibiotics are commonly used to treat pneumonia disease in order to alleviate this condition. Antibiotics, on the other hand, are ineffective in treating viral pneumonia, and antibiotic overuse can raise the risk of antibiotic resistance(Prayogo et al. (2020)). As a result, the number of needless anti-toxin prescriptions has increased, resulting in drug stockpile depletion and germ resistance. As a result, more explicit diagnosing tools must be created, as well as metrics that may be utilized to improve diagnostic performance.

The appearance of pneumonia on X-ray pictures is frequently ambiguous, and it can be mistaken for other illnesses or act like a variety of other benign abnormalities. These discrepancies resulted in a great deal of subjective decision-making and variation among radiologists when diagnosing pneumonia. As a result, automated assistance tools are required to assist radiologists in detecting pneumonia from x-ray images(Ayan and Unver ¨ (2019)). Recent advances in the field of deep learning, particularly convolutional neural networks (CNNs), have shown significant promise in image segmentation. The fundamental goal of CNNs is to create an artificial model that mimics the visual cortex of the human brain. The major benefit of CNNs is that, rather than handmade features, they may extract more relevant characteristics from the full image. It's causing a paradigm change in medical treatment, thanks to increased access to medical data and rapid advancements in analytics tools. Deep Learning has been shown to be an effective tool for improving analytics precision in hospitalized pneumonia patients

Keeping the issues in mind, a thorough diagnosis of the condition must be determined. Precise analysis can also be beneficial when choosing the best treatment for a patient, as misdiagnosis can cause delays in treatment. To address the significant problem of fatalities or providing genuine care as a result of this sickness, X-ray pictures must be inspected utilizing this revolutionary technology. With the help of deep learning technology, diagnosing these x-rays will become easier and faster, resulting in fewer human errors and more timely correct decisions. The use of image analysis and deep learning algorithms to detect illness has a wide range of applications. According to research1 done at Intermountain Healthcare and Stanford University, a new method based on artificial intelligence promises to be able to accurately detect important findings in chest X-rays of patients in the emergency room who have pneumonia in just a few seconds

With the aid of these approaches, we can assess performance on a variety of metrics and determine which criteria are most appropriate, which may then be applied to the area of healthcare. As life expectancy increases, coupled with global population data analysis in healthcare, it is poised to have a major impact on modern care. Healthcare analytics can be used to reduce the cost of care, reduce the incidence of anticipated disease, prevent preventable disease, and generally improve patient care and quality of life. This technique has enormous promise in evaluating other types of images and in other healthcare departments, which became the driving force behind this study.

2 Literature Review

Until now, there has been no convincing technique for preventing lung abnormalities such as cancer and pneumonia. As a result, the first steps to limiting the risk of suffering are early diagnosis and reliable screening procedures, which are the most timely signs of lung problems. In this part, we'll take a look at some of the most notable contributions in the current literature.

2.1 Machine Learning Algorithms for Pneumonia Classification

Pneumonia has remained one of the illnesses that has sparked increased scientific interest in recent years. A research by (Muhammad et al. (2021)) where authors have used various deep learning models to extract useful features such as CNN, AlexNet, SqueezeNet, VGG16, VGG19 and Inception V3. After extracting the features classification models have been applied to diagnose the disease. The classification models include KNN, SVM, Naive Bayes and ANN. From the experimental results authors obtained that the Inception-V3 and ANN models performed best to give the highest accuracy of 97.19And also, for future work author included that developing an IoT based realtime daignosis of pneumonia can be done.

Eid and Elawady (2021) adapted a different approach where pre trained convolutional neural network was used for the extraction of features from the X-ray images and further boosting machine learning algorithm for the classification task namely Support Vector Machine(AdaBoost-SVM). The pre-trained CNN model used in the research was ResNet. This approach was proposed by author to overcome the training time for better performance and lower error rates. From the simulation results, author concluded that the proposed approach gave better results when compared to other CNN off the shelf models. And for future work, they hope to improve the model and further add the diagnosing of multi-grade diseases.

A similar study(Yee and Raymond (2020)) where Inception V3 CNN model was utilized for feature extraction and on those features three machine learning classification algorithms were used to predict pneumonia. The machine learning algorithms were Neural Network, Support Vector Machine and K-Nearest Neighbors. The performance of these models were measured using the confusion matrix, specificity, sensitivity, precision and recall. The results showed that the Neural Network gave good overall performance in 3 terms of accuracy, precision and recall when compared to other two models. Neural Network achieved highest sensitivity of 84SVM has the highest AUC score of 93

In research(Alqudah et al. (2020)), authors also developed a CNN model to extract the features from the images where each feature is responsible for the each class. After feature extraction, different classification algorithms are used to classify the disease. The authors have utilized K-Nearest Neighbors and Support Vector Machine using K-Fold techniques. The classification results are evaluated on different metrices namely accuracy, precision, sensitivity and specificity. The proposed method outperformed other baseline methods to give higher performance and achieved accuracy of 94(2013)) was carried out which extended the previous work PneumoCAD, computer based diagnosing system and here, authors main objectives were to improve accuracy and performance in detecting pneumonia in infants. Proposed research was done with the help of three classifier machine learning models namely K-Nearest Neighbor(KNN), naive Bayes and Support Vector Machine(SVM). First texture based features in the images were extracted from the chosen dataset and then with the help of algorithms classification was carried out and resulted where SVM outperforms the other models. Authors concluded that the SVM classifier showed more stable performance with variations in training and also outperforms the previous work which this research is based upon.

2.2 Deep Neural Networks for Pneumonia Classification:

Machine learning techniques such as SVM, Random forest, and others are frequently used for general classification problems. Researchers have begun to use deep learning approaches exclusively for image segmentation and contextual marking challenges in the medical sector, namely for detecting pneumonia from X-ray images. To improve the diagnostic performance for a certain condition, various neural networks with varying layers of networks are directly applied on the input data such few studies are discussed below on similar approaches.A research(Dossou et al. (2020)) where authors has explained how the AI can shape the healthcare field in coming future with the advancements and help in detecting pneumonia using X-ray images. A CNN model was developed which performed really well with accuracy of 91.04pneumonia at an early stage. Authors have also addressed the technical, legal, ethical and other logistical concerns with their solutions which will come handy in ensuring availability of this growing technology

Another research(Li et al. (2019)), where authors developed a model that can automatically detect pneumonia in CXRs consisted of convolution filters between each of the convolutional layer and compared the results with the transfer learning models namely AlexNet and VGG16 which required more parameters compared to the proposed model. The research was carried out using the PneuX-rays dataset which was collected from the Hospital based in China. Preprocessing of the dataset was done before splitting the data into test and train. Authors found that though the transfer learning models shows good results but they also focuses on the unrelated regions of the lungs in images which they improved in the developed neural model which primarily focuses on the exposed region and extracts more features related to pneumonia and thus performs better.

In research(Rajpurkar et al. (2017)), authors developed an algorithm named, CheXNet which consists of 121 layers of convolutional neural network and concluded that the developed model showed par performance in classification of pneumonia on both sensitivity

4 and specificity level. Also an extension in the developed model outperforms previously developed models on the largest developed dataset; ChestX-ray14. The authors also found some limitations to the research as prior examinations or history of patients were not permitted to be used and also only the frontal radiographs were available for the diagnosis and that decreases the chances for diagnosing.

Mao et al. (2020) developed a model using deep learning which is mainly based on ensemble Mask R-CNN and RetinaNet. Three models were designed RetinaNet, Mask R-CNN and combination of RetinaNet and Mask R-CNN. From the results it was concluded that the ensemble model based on combination of RetinaNet and Mask R-CNN is superior to both other models. Though the result showed good performance, authors concluded that the detection is still not up to the mark as it can happen mainly because of two reasons. First is that there are insufficient training samples, and the second that the location of pneumonia is very small, making identification difficult. A similar research(Habib et al. (2020)), where authors also developed an ensemble model for the feature extraction with Random Forest as an classifier for predicting pneumonia. The deep learning models CheXNet and VGG19 are combined together to extract the features from the X-ray images and further various machine learning algorithms are used for the classification task. The machine learning techniques used are Random Forest, Adaptive Boosting, K-Nearest Neighbors and for the irregularity of the dataset Random Under Sampler, Random Over Sampler and SMOTE is applied on the feature vector. Among these models, Random Forest is found to be performing best and outperforms other models providing 98.93the model so that it can effectively categorize two or more illnesses.

A different approach by Kaushik et al. (2020) where different models with different number of convolutional layers were used, One, two, three, and four convolutional layers were used in the first, second, third, and fourth models, respectively. Dropout regularization was applied in the second. third and fourth model to reduce overfitting. Developed models performance was measured over confusion matrix,accuracy graphs and loss graphs. First and Second model underperformed compared to third and fourth model. Third classifier model performed best among all the four models with the least amount of overfitting and the best accuracy and recall. A similar research(Shah et al. (2020)), where authors developed a CNN model with a smaller number of convolutional neural layers. The proposed deep learning model classified the disease in an accurate manner. Data augmentation and preprocessing stages carried out during the proposed method ensured that the model is not prone to overfitting and obtained results remains consistent.

A study conducted by Militante and Sibbaluca (2020) where several models were used to determine the best model for diagnosing pneumonia. This study used five different pre trained models of CNN namely AlexNet, GoogleNet, LeNet, VGGNet and ResNet. The authors utilized RSNA dataset used in Kaggle Pneumonia Detection Challenge. Input images were resized to 224x224 dimension for all selected models. Parameter-tuning was done for every model to produce apt results. ResNet model achieved the least accuracy of 7495future studies, author proposed to use other pre-trained convolutional neural network such as Inception-v3, MobileNet and ShuffleNet with experimentation in hyper parameters to improve performance.

In this research(Nath and Choudhury (2020)) authors used transfer learning approach to develop a method to predict the severity of the disease pneumonia. The VGG16 al5 gorithm has been used and several last layers of the model has been fine tuned to accurately classify the images. The dataset chosen was imbalanced and the data augmentation techniques has been applied. The results obtained has been compared with the CheXNet model and it shows that the proposed model has achieved higher results in comparison. The developed model achieved an accuracy of 93to other models. And authors have also proposed future work which can be developed using other pre trained models like ResNet, AlexNet and Inception.

A similar research of ensemble learning model was done by Asnaoui (2021) where model consisted of three fine-tuned versions of InceptionResNet V2, ResNet50 and MobileNet V2. The authors aimed to evaluate the results of ensemble model as well as single models for the classification. The data augmentation techniques are applied to the dataset where rescaling, rotations, shifts, shears and zoom strategies were utilized. For a single model authors found InceptionResNet V2 gave good performance of 93.52score. and further ensemble model performed the best wen compared to all models with F1 score of 94.84can be improved using several other datasets and more feature extraction techniques.

3 Methodology

Implementing the recommended strategy for the research requires a well-planned methodology. In this section, various steps have been followed for the research as described and summarized in Figure Implementing the recommended strategy for the research requires a well-planned methodology. In this section, various steps have been followed for the research as described and summarized in Figure

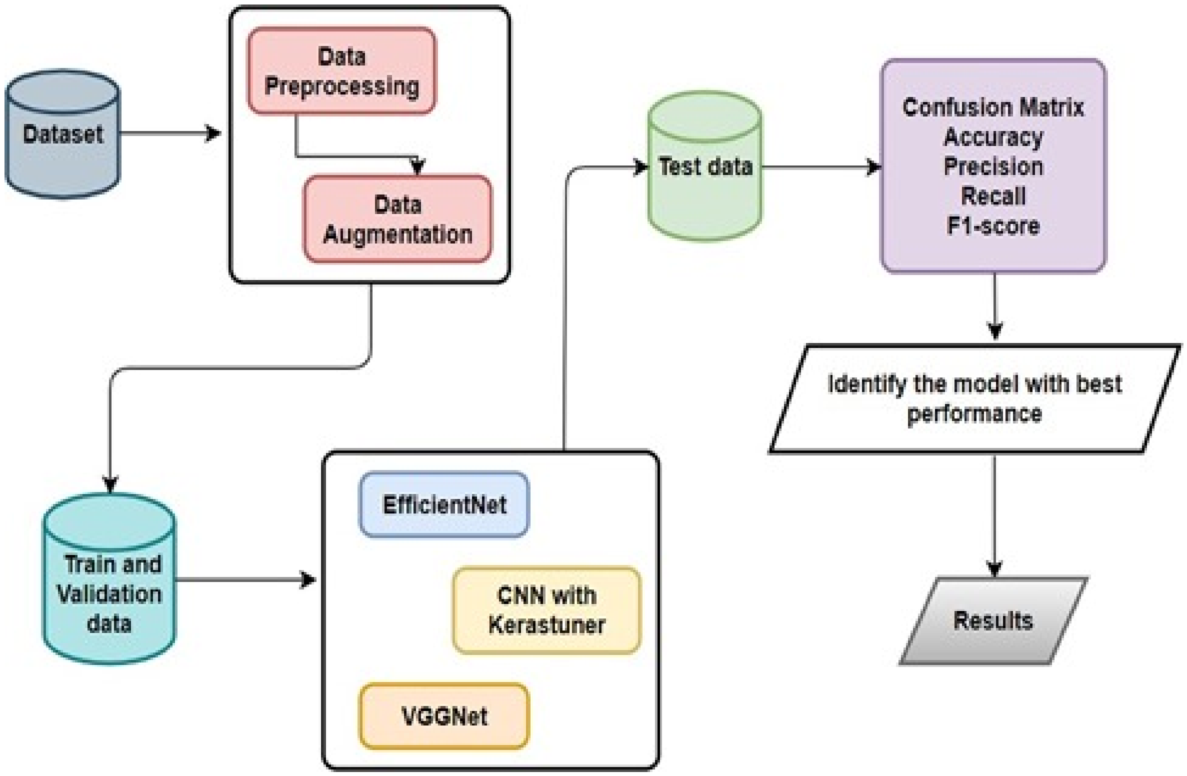

Figure 1: Block Diagram of proposed research

3.1 Data Selection and Description:

The goal of this research is to categorize images that have been impacted by pneumonia. For this research, x-ray images dataset2 was chosen which consists of 5856 chest X-ray Images provided by the authors. The dataset has been made publicly available for the research purposes. The dataset was divided into two classes: pneumonia and normal, and it was further divided into three stages: training, validation, and testing to carry out the research. Figure 2 shows some X-ray image samples from dataset. The goal of this research is to categorize images that have been impacted by pneumonia. For this research, x-ray images dataset2 was chosen which consists of 5856 chest X-ray Images provided by the authors. The dataset has been made publicly available for the research purposes. The dataset was divided into two classes: pneumonia and normal, and it

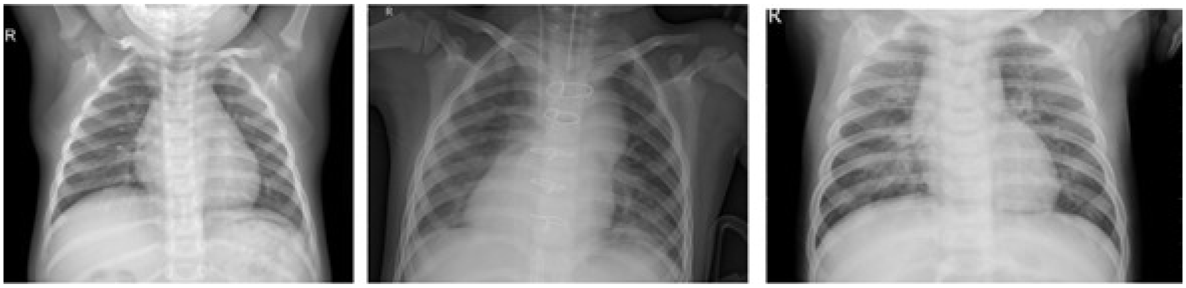

Figure 2: X-ray

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3.2 Data Preprocessing:

Before using any machine learning model, it is also necessary to convert data into acceptable formats. Real-world data contains noise, and dealing with it increases processing time while also lowering classification accuracy. As a result, data transformation is a critical stage in the process.

3.2.1 Data importing into Google Colab:

The dataset was downloaded in.zip format on a local workstation and then uploaded as a zipped file to Google Drive. The.zip file was then unzipped on Google Drive to prevent re-uploading the dataset each time the generated code was run, as well as to reduce the time it took to read the data through the Colab worksheet.

3.2.2 Data Augmentation:

To get a trustworthy result, deep learning requires a large amount of data. However, in certain cases, there may be insufficient data. Obtaining and annotating data, particularly for medical issues, is a costly and time-consuming procedure. Fortunately, there are a few options for resolving this issue. One of them being, data augmentation which can enhance the accuracy of the deep learning methods(Ayan and Unver (2019)). In this ¨ study, data augmentation was applied on the training data. Different augmentation techniques was used such as rescaling, zooming, rotating and flipping. Overall, data augmentation improves the model's capacity to extrapolate and helps avoiding overfitting. To expand the data for training the model, the following actions were taken

- Image Rotation: The pictures were rotated by 0, 90, 180, and 270 degrees, respect ively. Each rotation had a 25
- Image Flipping: The pictures were flipped left, right, or up-down at random. For data extension, the flipped pictures were subsequently included to the dataset.TensorFlow's random flip left right and random flip up down functions was used to accomplish this.
- Zooming: The images were zoomed with range of 0.2 to focus the affected area more and to select the focused part of the image.

4 Implementation

Three different deep learning models were implemented in this research for accurately classification of pneumonia from X-ray images. The first and second model were developed using the technique called transfer learning and the third model was custom designed CNN model which was implemented using Kristine that helped in selecting the hyper parameters automatically.

4.1 Transfer Learning

Pre-trained models are used for the initial phase in transfer learning, rather than going through the time-consuming process of training models with self-assertively instated loads. As a result, it will aid in the conservation of significant resources that would otherwise be required to develop neural network models to address these challenges. The significant cost of constructing large CNNs may be avoided by using transfer learning(Fu and Aldrich (2018)). In this research, we have used the fine-tuning approach which is motivated by changing the layers or adding some layers on the pre-trained models. We have used two well-known CNN networks VGGNet and EfficientNet for this study.

4.1.1 4.1.1 VGGNet:

Simonyan and Zisserman presented the VGG network design in their research(Simonyan and Zisserman (2014)) published in 2014. The pyramidal structure of this network is exemplified by the fact that the base layers, which are closest to the picture, are broad while the top layers are deep. The model consists of 16 convolutional neural layers with (3x3) receptive fields combined with five max pooling layers (2x2) and finally three fully connected layers with max activation function at the end. For this research, model with pre-trained weights on ImageNet was used and the more layers at the end of network were added. Also, the model has simple and efficient architecture which

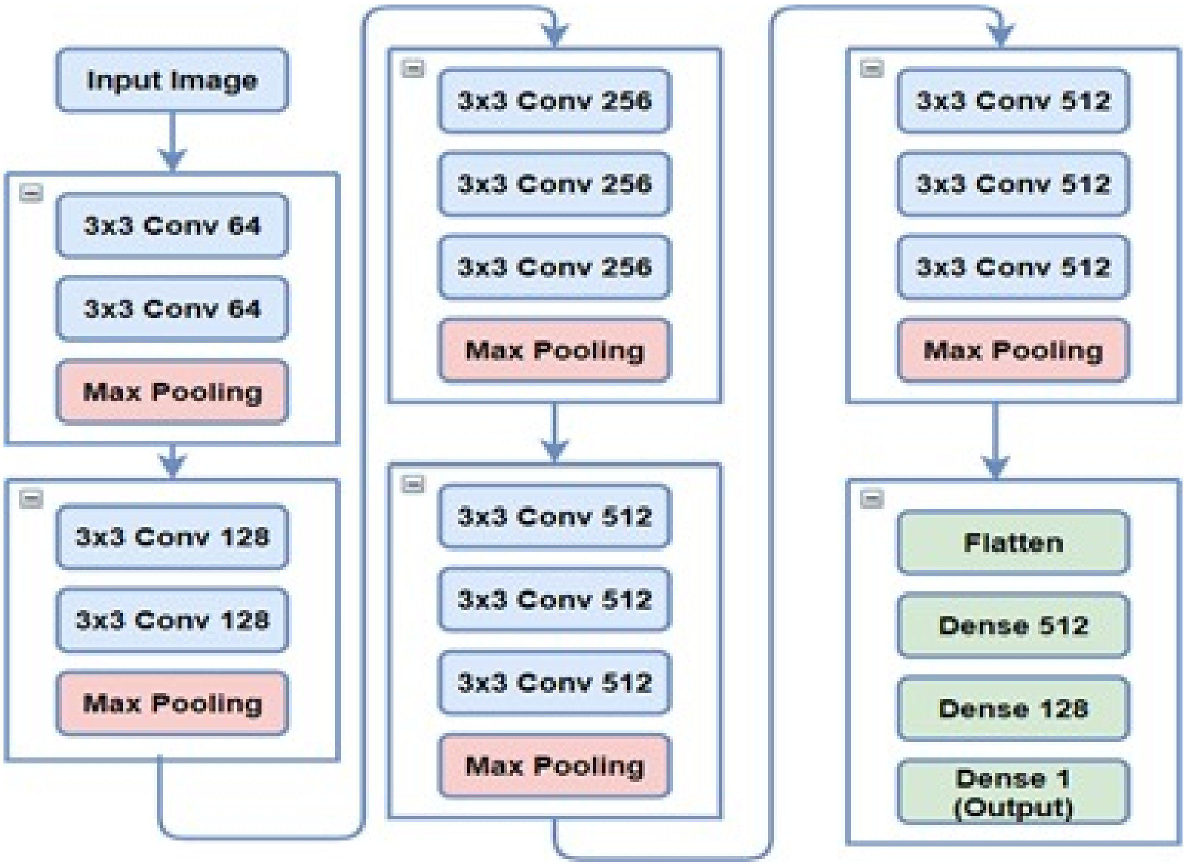

Figure 3: Fined Tuned VGG Architecture

makes it easy to use this model in a wide range. Below Figure 3 shows our modified network architecture.

4.1.2 EfficientNet:

In 2019, a new novel model was introduced by Google AI authors3 where they tried using a simple and highly effective coeficient to scale up conventional CNN models and it's available from Github respositories. It uses compound scaling method to surpass the state of the art models with 10 times accuracy while maintaining model efficiency, used for transfer learning datasets. Compound scaling method performs grid search between different dimensions of the network to find the appropriate coefficients and then those coefficients are used to enhance the baseline network. This proposed approach helps improves models performance. And to further improve the effectiveness, a baseline model EfficientNet is developed with the below architecture as shown. EfficientNet offers models ranging from B0 to B7, with parameters ranging from 5.3M to 66M. For this study, EfficientNetB4 model was used for the transfer learning process with 19M parameters and global average pooling layer was added to reduce the overfitting and in addition to that a sequence of two dense layer were added with reLu activation function.

Finally, an output dense layer was added with sigmoid function. Below Figure 4 shows the modified

4.2 Convolutional Neural Network(CNN):

Yann LeCun4 introduced CNNs, commonly known as ConvNets, in the 1980s. CNN's main advantage is that it is capable of detecting significant highlights without the need for human intervention. CNN is made up of many layers that are layered together and use a local link called a local receptive field and weight-sharing to improve execution and efficacy. CNN's main advantage is that it is capable of detecting significant highlights without the need for human intervention. CNN is made up of many layers that are layered together and use a local link called a local receptive field and weight-sharing to improve execution and efficacy. CNN's main advantage is that it is capable of detecting significant highlights without the need for human intervention. CNN is made up of many layers that are layered together and use a local link called a local receptive field and weight-sharing to improve execution and efficacy.

Below Figure 5 helps to show the working and architecture of proposed model.

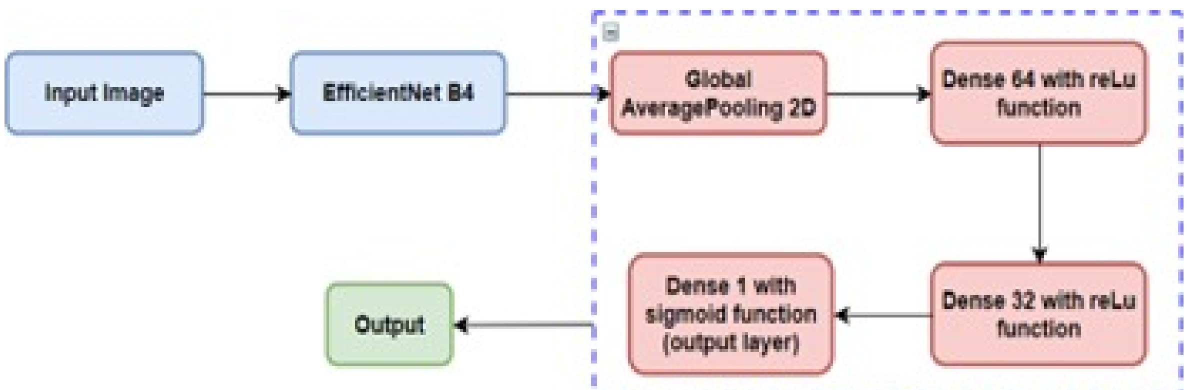

Figure 4: Fined Tuned EfficientNet Architecture

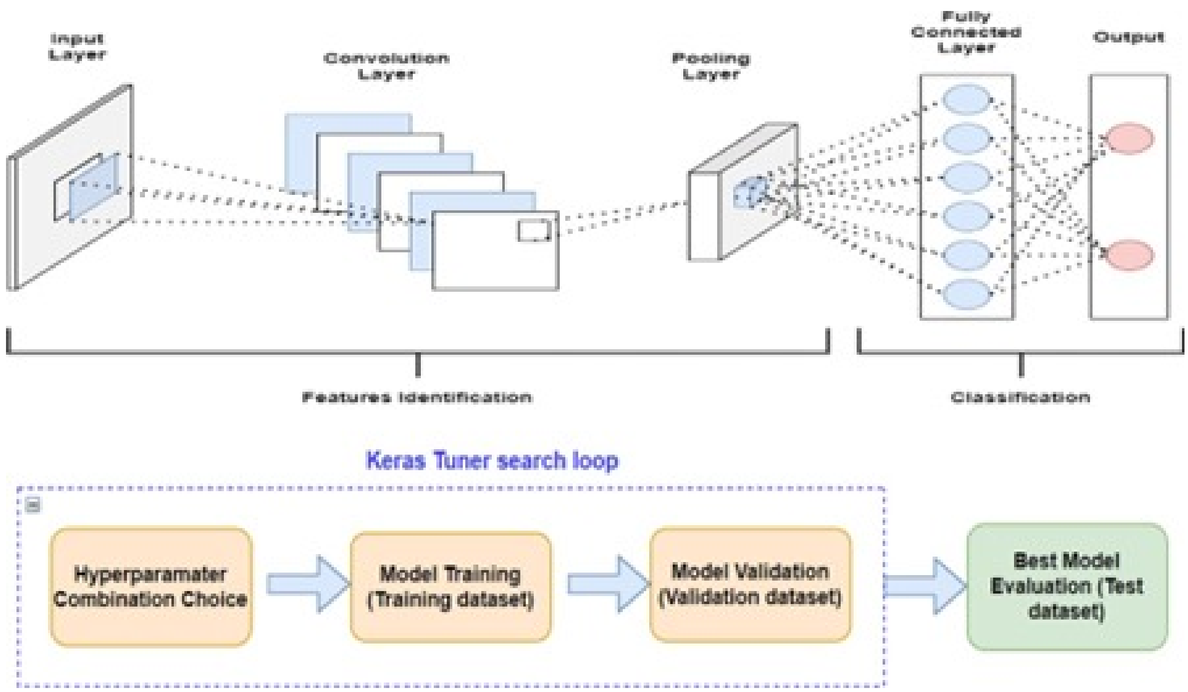

Figure 5: CNN architecture with Hyper parameter tuning process

5 Evaluation

In this research, performance measures such as accuracy, recall, precision, and f1 score were used to assess the suggested models. The confusion matrix convention was used to form the metrices where tn, fp, fn, tp represents the number of true negative, false positive, false negative, true positive respectively.

The performance of these models will be measured using specific metrics measures. The performance of these models will be measured using specific metrics measures depending on the values in the aforementioned matrix. T he metrics' formulae are asfollows:

Accuracy = (tp + tn)/(tp + fn + fp + tn)

Precision = tp/(tp + fp)

Recall = tp/(tp + fn)

F1-Score = 2 x (precision x recall)/(precision + recall)

5.0.1 Transfer Learning- VGG:

The fined tuned VGG model was able to achieve an overall test accuracy of 92.09 and train accuracy of 99. F1 score of the model was 0.99. The summary and learning curves of the model are shown in Figure 6 and Figure 7 respectively

```
Model: "sequential"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
vgg16 (Functional)           (None, 8, 8, 512)         14714688
_________________________________________________________________
flatten (Flatten)            (None, 32768)             0
_________________________________________________________________
dense (Dense)                (None, 512)               16777728
_________________________________________________________________
dense_1 (Dense)              (None, 128)               65664
_________________________________________________________________
dense_2 (Dense)              (None, 1)                 129
=================================================================
Total params: 31,558,209
Trainable params: 23,922,945
Non-trainable params: 7,635,264
```

Figure 6: Summary of the fined VGG pre-trained model

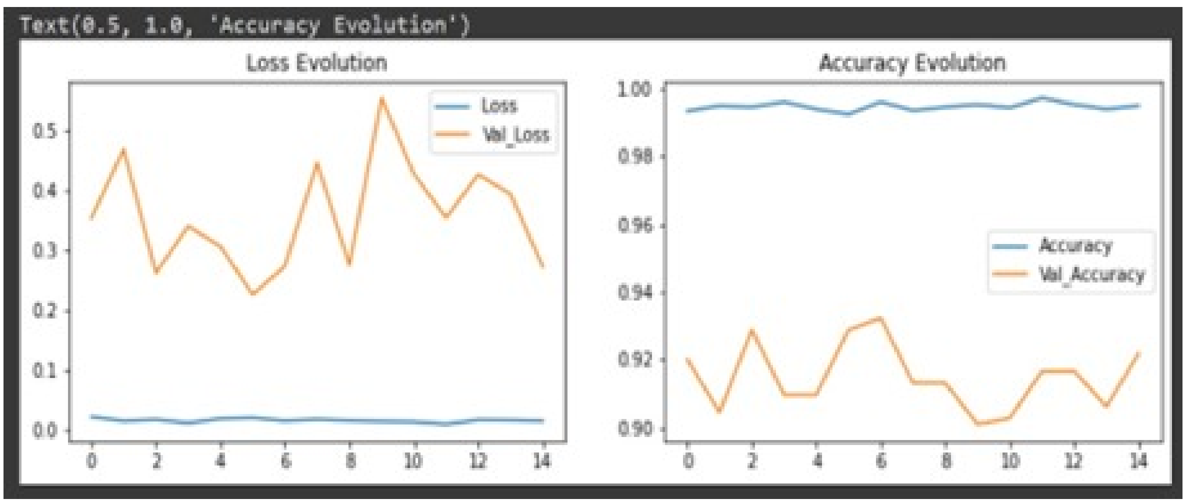

Figure 7: Learning Curves of the pre-trained VGG model

5.1 Transfer Learning- EfficientNet

The fined tuned EfficientNet model was able to achieve and overall test accuracy of 98The learning curves of the model based on training and validation dataset can be seen in below Figure 8. The confusion matrix for the model has been presented in the Figure 8. The precision and recall of the model came out to be 0.97 and 0.96 respectively. The F1 score achieved for the model was 0.98.

5.2 CNN with Kerastuner:

First a CNN model was developed and using that model, tuner search was performed on the model to find the best parameter values for the model. From Figure 9, before and after description of the parameters an be found once the tuner search is done. After

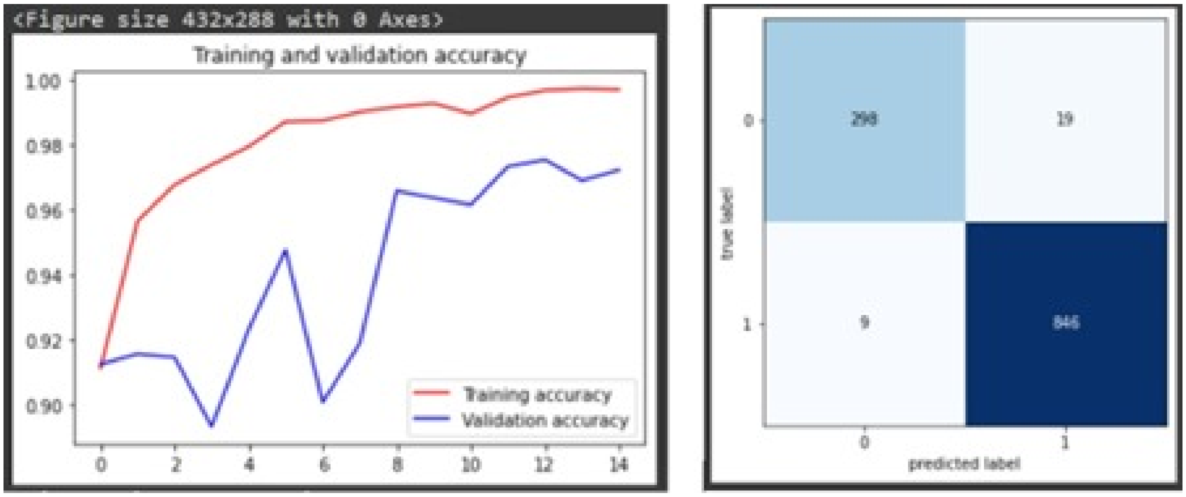

Figure 8: Learning Curves and Confusion Matrix of the EfficientNet model

```
Model: "sequential"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
conv2d (Conv2D)              (None, 126, 126, 32)      896
_________________________________________________________________
max_pooling2d (MaxPooling2D) (None, 63, 63, 32)        0
_________________________________________________________________
conv2d_1 (Conv2D)            (None, 61, 61, 32)        9248
_________________________________________________________________
max_pooling2d_1 (MaxPooling2 (None, 20, 20, 32)        0
_________________________________________________________________
flatten (Flatten)            (None, 12800)             0
_________________________________________________________________
dense (Dense)                (None, 100)               1280100
_________________________________________________________________
dense_1 (Dense)              (None, 1)                 101
=================================================================
Total params: 1,290,345
Trainable params: 1,290,345
Non-trainable params: 0
```

```
Model: "sequential"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
flatten (Flatten)            (None, 49152)             0
_________________________________________________________________
dense (Dense)                (None, 256)               12583168
_________________________________________________________________
dense_1 (Dense)              (None, 10)                2570
=================================================================
Total params: 12,585,738
Trainable params: 12,585,738
Non-trainable params: 0
```

Figure 9: Summary of the model "Before" and "After" Hyperparameter tuning with Kerastuner

completing hyperparameter search, optimal learning rate value found to be 0.01 and the best epoch values came out to be 7. And once these parameters are found, new model with the new parameters was built where the training accuracy came out be 96test accuracy of 76from Figure 10.

5.3 Results and Analysis:

The results of the experiments and the specifics of the implementation will be discussed in this section. The validation and test findings acquired, as well as the explanations for the experimental work utilized. To begin with, we wanted to compare the architecture and results of our models with the state of the art models which has been previously used for the pneumonia detection to know a glimpse of each network performance.

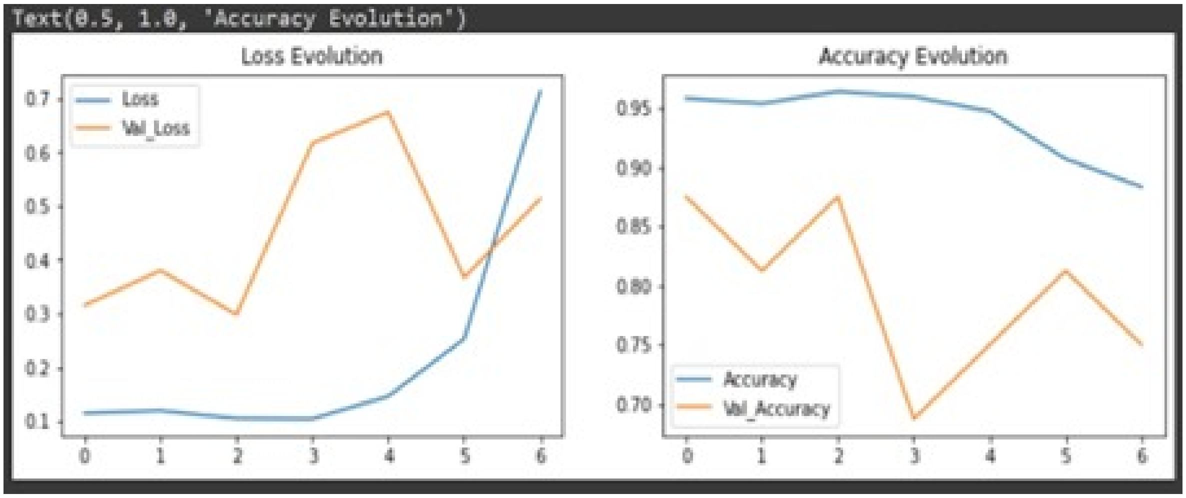

Figure 10: Learning Curves of the CNN-kerastuner model r

Method	**Technique**	**Accuracy**
Proposed Method	VGG16 Transfer Learning	92.09%
Proposed Method	EfficientNet Transfer Learning	98%
Proposed Method	CNN with Kerastuner	76%
Militante and Sibbaluca (2020)	AlexNet	95%
Militante and Sibbaluca (2020)	ResNet	74%
Asnaoui (2021)	Ensemble ChexNet & VGG19	97.8%

Table 1: Comparison of different methods and techniques for pneumonia classification.

The performance of the three models namely: VGG and Efficient Net using transfer learning and the third CNN model with kerastuner has been assessed. The two models developed using transfer learning achieved highest accuracy rate 92for Efficient Net models whereas the CNN model with kerastuner achieved the accuracy of 76respectively and also for the Efficient model is 0.98, 0.98 and 0.98 respectively. The experiments were performed in Google Colab notebook with GPU and memory of 12GB. The augmentation technique was also applied to the training set to increase the dataset by applying rotation, flipping and zooming. Adam optimizer has been utilized for these models and binary cross entropy for the loss function. From the defined mertices, the transfer learning models gave the higher performance when compared to the CNN model developed using kerastuner. According to the accuracy achieved and f1 score and also keeping in mind the other metrices, transfer learning Efficient Net model gave the best results and performed well when compared to other models.

6 Conclusion

This study investigates the usefulness of deep learning in diagnosing pneumonia using three convolutional neural network models. Every CNN model is physically evaluated and fine tuned in order to use the framework for the classification. The x-ray images dataset was acquired and our study enables to identify the best performing model to detect pneumonia. To overcome the time consuming process of developing a new model from ground up and also finding the best parameters for the model, two different approaches were used in this study. Firstly, two model were developed using the transfer learning technique and the other technique utilized the kerastuner for finding the best hyperparameters for the model. The models using transfer learning used pre-trained weights on ImageNet as initialization for the new models. Furthermore, more layers at the end of the models were added. Also, new model using kerastuner was developed with minimize the binary cross entropy function. With the help of transfer learning method, we overcame the problem of having a large dataset and also reduced the time consuming process of making new models from the scratch. Moreover, with the help of kerastuner, we utilized an approach of selecting hyperparameters without going through the process of hit and trial and training the model again and again which is also a time efficient method. Developed methods outperforms the baseline models and the state of the art previous results in performance measures. The EfficientNet model using transfer learning achieved highest accuracy of 98that the proposed model is quite faster when compared with baseline models. According to the experimental results and metrices formed, every model has its own detection capability on the dataset. However among these models, Efficient Net using transfer learning showed best performance

In the future work, other model using transfer learning can be applied. However, an ensemble network using the Efficient Net and kerastuner can be formed to enhance the performance of the model. Though in the defined network, kerastuner was not able to show its highest performance due to number of reason and was prone to overfitting but in future work, that can be resolved. And also, keeping in mind the computational limit and power consumption, these models were run in Google Colab and for the further extension of the work it can be done to improve and use more power and TPU environment to process the models.

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