Detection of Pneumonia using Resnet Models

MSc Research Project
Data Analytics

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Detection of Pneumonia using Resnet Models

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Abstract

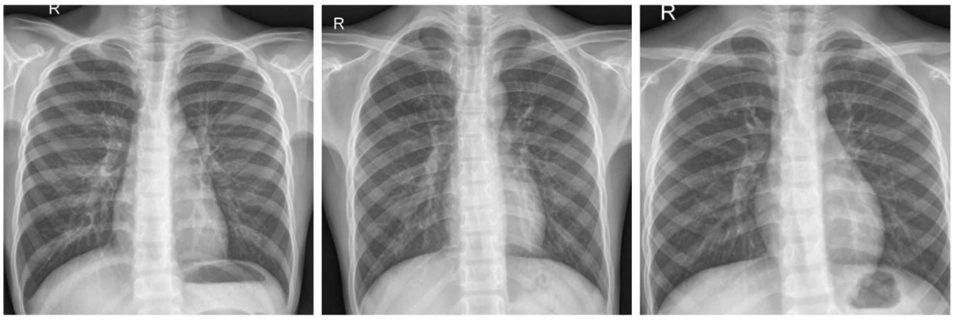
Pneumonia is a lung disease which mostly affects the children and old aged people. To detect the presence of pneumonia in a fast way deep learning was introduced using x-ray images. In the past several deep learning models were implemented, whereas in this paper a specific model with various layers is implemented. This research studies the difference between the four residual networks (Inception-Resnet, Resnet-152,Resnet-101 and Resnet-50) and also to detect the disease pneumonia. The four models were evaluated using different metrics such as accuracy, precision, recall and F1-score. Even though the four models gave almost same accuracy, the F1-score of Resnet-152 outperforms all other models with a F1-score of 57 percentage with a train accuracy of 95 percent and 89 on validation accuracy.

1 Introduction

One of the common and dangerous disease in the day-to-day life is pneumonia which is a similar type of disease like covid which spreads from one person to another through air which affects one million people per year (Irfan et al.; 2020) in united states alone. This disease is also an air-borne disease which affects the person's lungs with symptoms starting from cold, uneasiness to breathe and even may end up in death in worst case scenario. Pneumonia disease could be broadly categorized into two types which are viral pneumonia which is caused by virus and the other category is bacterial pneumonia which is caused by the bacteria.

It could be tested with the use of Polymerase chain reaction (PCR Test) which is not available on all areas of the world and the lack of PCR Test kits due to the high patient number caused during the covid pandemic forces to find a new and quick method to detect the disease. In the past similar methods used by (Arora and Sharma; 2021) to detect several diseases (Riri et al.; 2016) have been detected with the help of deep learning models which has been trained to detect whether a person is affected or not with the help of X-ray images which are available more than PCR Test kits and it also gives result in a fraction of minute also without the possibility of human errors.The resnet models are specifically chosen for their ability to skip connections which removes the possibility of gradient problem.

Sample images of normal and pneumonia infected lungs in the dataset used are shown in the below images.



(Fig:1) X-ray image of Normal Lungs

(Fig:2) X-ray of Pneumonia Affected Lungs

Every Research should have a benefit out of it which could be used in the real world. In this research it could be used to reduce the time taken [When compared with PCR Test] to find out whether a person is affected with pneumonia or not and to reduce the cost where a PCR test is required for each person and also to study the differences between the different type of resnet models and their characteristics which are applied on same dataset with same data pre-processing methods.

1.1 Research Question

How accurately the disease pneumonia could be detected from the x-ray images using different types of residual network algorithms?

1.2 Objective

The main goal of this research is to detect the presence of pneumonia in the x-ray images of patient lungs using four types of residual networks namely resnet-50, resnet-101, resnet-152 and Inception-resnet with less time and cost consumption and also to study the difference between these models.

Following to the Introduction section, Section 2 discusses about Related work followed by Methodology, Design Specification, Implementation, Evaluation and Results and Conclusion.

2 Related Work

2.1 Healthcare

In this section of literature review various diseases detected using the deep learning with the help of images of the affected parts are discussed along with their advantages and disadvantages:

A research was carried out in 2021 with five different models Random Forest Classifier and SVM along with three deep learning architectures VGG16,Inception V3 and Resnet using the MRI images of patient's brain to classify the brain tumour where it shows that the deep learning models outperform the machine learning models with VGG16 performs well than other models with a Accuracy of 90 percent which could be improved by using different optimizers and cross validation.

A group of researchers tried to detect the dental problems of patients using deep learning, where in that research paper it focuses on the dental images of mold, intra-oral, extra-oral and radiographic images of various patients with a four level tree structure which contains 19 sub categories. Due to the various sub categories and tree structured, a tree structured algorithm is required where the decision tree is implemented. Eventhough the model works perfectly fine with good results it could be tested on a larger dataset in the future to see it's efficiency where in this research it has been applied on a dataset which contains only images of 50 patients with also an addition of any neural network architecture.

A similar research was executed in 2018 to detect the presence of Alzheimer (Fuse et al.; 2018) with the brain image of patient's with the help of SVM (Support Vector Machine) model where the features are extracted using P-Type Fourier Descriptor and image slicing where it gave a 87 percent of accuracy on two of the six intracranial volume. In the future it could be used with various type of feature extraction methods along with various new neural networks.

These healthcare related problems could be tried with various optimizers and hyper parameter tuning, so that they could produce better results in the future.

2.2 Pneumonia

In this section, the various methods used to detect the particular disease pneumonia using deep learning models are classified:

A group of two in 2020 did a research (Serte and Serener; 2020) to detect the three types of pneumonia namely viral pneumonia, bacterial pneumonia and mycoplasma pneumonia to discreening covid-19 from these three pneumonia types where VGG outperforms all other algorithms with a accuracy of 80 along with an AUC of 87 percentage, sensitivity of 94 percentage and specificity of 71 percentage which is followed by other classification model such as Resnet model where six different neural networks are built namely VGG, Mobilenet-v2, Alex net, Squeeze net, Resnet-50 and Resnet-18. In this research the data could be augmented to get better results which could be executed in the future.

An advanced method has been discussed on this paper to find the severity of the pneumonia disease by (Darapaneni et al.; 2020) using chest X-Rays was done. It states that the detection of pneumonia with its place using localization (using Mask R-CNNs). In the future the proposed work could be executed along with the introduction of more effective and powerful localization methods such as YOLO (You Look Only Once). Unlike other paper, this paper only shows the idea of detection of pneumonia with the amount of lung opacity due to pneumonia.

This paper is an extended work of the previous paper by (Serener and Serte; 2020) where they distinguished the viral pneumonia and mycoplasma pneumonia with the covid-19 with the help of patient's x-ray images with seven neural networks namely Resnet-18, Resnet-50, Squeeze-net, alex-net, VGG, Dense-net and Mobilenet-v2.Among these seven architectures Resnet-50, Resnet-18 and Mobilenet-v2 models excel above the other models with an maximum accuracy of 76 between mycoplasma and typical viral pneumonia and an maximum accuracy of 81 percentage between mycoplasma and covid-19.

In 2018, an interesting study was conducted by (Deepika et al.; 2018) to identify the stages of lobar pneumonia, and pneumonia was classified into three stages: mild, moderate, and severe. In this paper they used a grayscale occurrence matrix to enhance the texture. The processed images are passed to his two architectures, support vector machines and neural networks, reaching up to 96 percentage in neural networks and 86 percentage in support vector machines. On this paper the data could be augmented before fitting in the models which would have result in better performance.

A group of three individuals tried to analyze the effects of pneumonia from chest X-rays taken from normal lungs (Arunmozhi et al.; 2021) using various pre-trained models (known as transfer learning) such as VGG, Resnet and Alexnet with 5 cross-validations to increase model accuracy. A survey was conducted to find lungs that had undergone Using cross-validation, Alexnet achieved an accuracy of up to 98 percentage, followed by VGG and Resnet. This study was conducted on a small dataset. Model accuracy may decrease if the study is conducted on a larger dataset.

In 2021, a study to classify the presence of pneumonia using transfer learning models such as VGG19, Xception and InceptionResnet-V2 by (More et al.; 2021) where a maximum of 94 percentage achieved in VGG19 followed by 91 percentage on InceptionResnet-V2 and 88 percentage on Xception Model. These models could have performed even better if the data has been augmented before fitting into the model. There's no data pre-process which could have resulted in better results.

In 2021, three researchers conducted a study(Abubakar et al.; 2021) to detect pneumonia and its type either viral or bacterial pneumonia from x-ray images with a hybrid model of SVM and Naasnet along with two other transfer learning models Resnet-50 and Resnet-101. The dataset is pre-processed by augmenting the images. The hybrid model shows better performance with a accuracy of 92 because of Naaasnet which acts as a new predicted layer which is then classified by SVM.

A radiological classification study was conducted examining different architectures used to predict childhood pneumonia (Singh et al.; 2021). This research paper focuses on 7 different architectures used in both deep learning and machine learning. This article does not attempt new architectures, but merely examines and reports on previous articles. These seven models are CNN, RNN, FNN, Logistic Regression, Linear Regression, Random Forest, Naive Bayes, KNN, and SVM.

A research study by two researchers (S. and Radha; 2021) tried to distinguish X-ray images of lungs affected by Covid-19, pneumonia lungs and normal lungs . This research paper states that the image pre-processing is done followed by the image is converted into gray for contrast amplification then converted back to normal image for augmentation and then trained, the trained dataset is fitted on convolutional neural network where a maximum of 95 is achieved on covid affected.

In 2019, a study was conducted comparing two transfer learning models, VGG16 and Xception, to classify given X-rays as pneumonia-affected or normal lungs by (Ayan and Ünver; 2019). It concluded that the Xception model outperformed VGG16 in sensitivity, normal as precision, and pneumonia infected as recall, whereas VGG16 was accuracy, pneumonia precision, F1 score, and specificity.This research paper focuses on only two deep learning models. In the future, more architectures may be explored and implemented in this study, resulting in more data processing.

In this section the detection of pneumonia is mostly detected using transfer learning models to study the difference in these models, but it could be tested on a specific model with various layers or through hyper-parameter tuning.

2.3 Hybrid Models

In this section of literature review the various hybrid models used in the modern world to classify images are discussed along with their advantages and disadvantages:

A group of researchers published a paper which focuses on classification of images with hybrid models with one of the newest methods where (Suganthi and Sathiaseelan; 2020) it compares the results of seven hybrid architectures namely CNN with Genetic Algorithm, Long-short Term Machine, K-Nearest Neighbour, Multi-layer Perceptron, SVM, Extreme Learning Machine and RNN (Recurrent Neural Network). In this research the hybrid model with a combination of CNN and Generic algorithm performs well with an accuracy of Ninety four percentage, but the models are executed on different datasets where the poor dataset could result in poor performance. In the future these hybrid models should be executed with the same dataset with same data pre-processing, so that the differences could be studied clearly.

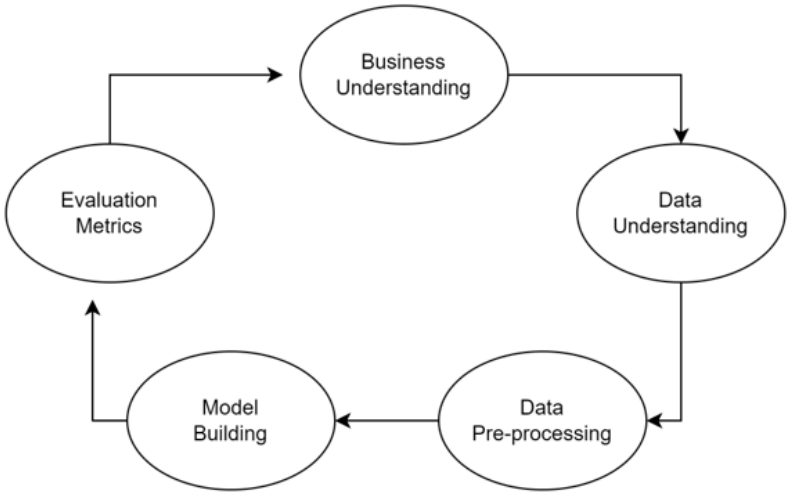
In 2018, an investigation was conducted to classify the brain tumour with the help of MRI Images by (Kumar et al.; 2018). The research was executed on a dataset with three fifty four images where in future a larger dataset could be used. To detect the brain tumour a hybrid of Support vector machine with particle swarm optimization algorithm which gave an accuracy of ninety five percentage which is compared with the normal support vector machine, the result shows that without the bio-inspired algorithm it gave just an accuracy of eighty six percentage. The hybrid model not only gives better accuracy but also with better specificity and sensitivity when compared to the SVM.

A research that sought to contrast the CNN, Extreme Learning Machines, CNN-ELM, and a advanced model of CNN-ELM called Ensemble CNN-ELM by (Kannojia and Jaiswal; 2018) where a CNN and ELM exist for each classifier in that model. Although the ensemble improves accuracy, it does not make much difference in model accuracy. In the future CNN-ELM model could be built with various hyper parameter tuning.

The most common problem faced on this section of previous work is the lack of augmentation which could be filled in the future and see the difference between the augmented and non-augmented data.

3 Methodology

In this research the Knowledge Discovery in Database Methodology commonly known as the KDD Methodology will be used. The KDD Methodology consists of five different steps which have been shown in the diagram below:



(Fig:3) KDD Methodology

At first the problem should be understand like what the business wants and how could it be improved for this the problem and scenario should be seen from the overview. The overview could be understood only when the problem is seen from both sides the client and the supplier.

3.1 Dataset

3.1.1 Dataset Selection

The dataset used in this research is from kaggle website an open-website.The dataset contains images of x-ray of normal and pneumonia affected lungs.[1] The selected dataset is an imbalanced dataset which has been already splitted into train and test data.This dataset contains two sections 5232 images on the train data and 624 images on test data.

3.1.2 Exploratory Data Analysis

In this part the data is clearly studied through Exploratory Data Analysis (Commonly known as EDA) where the data is expressed in a diagrammatic representation so that it could be easy to understand. In this research, a diagrammatic representation of the two classes are shown which displays the number of images on each class is executed.

3.1.3 Pre-Processing

Then the clearly studied data is augmented with different augmentation techniques, which is nothing but making small changes in the pictures so that the model could understand more features from the images given to it to understand. By implementing augmentation the model could give improved results.

With the help of Image generator function various augmentation techniques are executed on the train dataset. A variety of data augmentation techniques used in this research are height and width ranges are shifted by 0.2 with shear and zoom range also changed by 0.2 with horizontal flips and rotation flip of 40 likewise in (Budhiman et al.;

[1]https://www.kaggle.com/datasets/andrewmvd/pediatric-pneumonia-chest-xray

Model Name	Epochs	Layers	Optimizer
Resnet-50	10	50	Adam
Resnet-101	10	101	Adam
Resnet-152	10	152	Adam
InceptionResnet	10	164	Adam

(Table:1) Model Information Table

2019) .These are the augmentation techniques used in this research. Since the dataset is already solitted into train and test there's no need for dataset splitting.

3.2 Model Building

The pre-processed data will be fitted in the different models which have been built already in this part. This research uses transfer learning, which is the process of using pre-built neural networks.In this article, we employed different Resnet models to detect the possibility of pneumonia using four different Resnet models which have different number of layers namely Resnet-50 (Generic Resnet model), Resnet-152, Resnet-101 and inception-resnet-V2 are hybrid models of inception and resnet containing 164 layers with same number of Epochs(In this case 10 Epochs will be used) along with same loss function categorical cross-entropy and same optimizer. All these models are added with a flatten layer and dense layer on top of it. In the past, leaves were classified in various fields of agriculture (Li and Rai; 2020), while in the medical field various resnet models were used to classify other diseases such as dental in (Li and Rai; 2020) and lung diseases by (Zakaria et al.; 2021). This allowed us to investigate different Resnet models simultaneously.

3.3 Evaluation Metrics

And once the model is fitted, the efficiency of the model is known through different evaluation metrics. Evaluation metrics are used to decide how good a model is which has been built. In a wide range of evaluation metrics, the metrics which are implemented in this paper are as follows:

- Accuracy

  Accuracy is the overall predictions correctly predicted by the model on the training dataset which is a important classification type evaluation metric.

- Validation Accuracy

  Validation accuracy is the number of predictions predicted correctly on the test dataset.

- Confusion Matrix

  Confusion matrix is a matrix which contains the values of predicted values and true values in a 2x2 matrix containing true positive, false negative,false positive and true negative.

- Precision

  Precision is the number of positive class predictions made in the model.It is calculated from the values of confusion matrix.

Precision = True Positive/(True Positive + False Positive)

- Recall

  Recall is the number of positive predictions made in the whole classes.It is calculated from the values of confusion matrix.

  Recall = True Positive/(True Positive + False Negative)

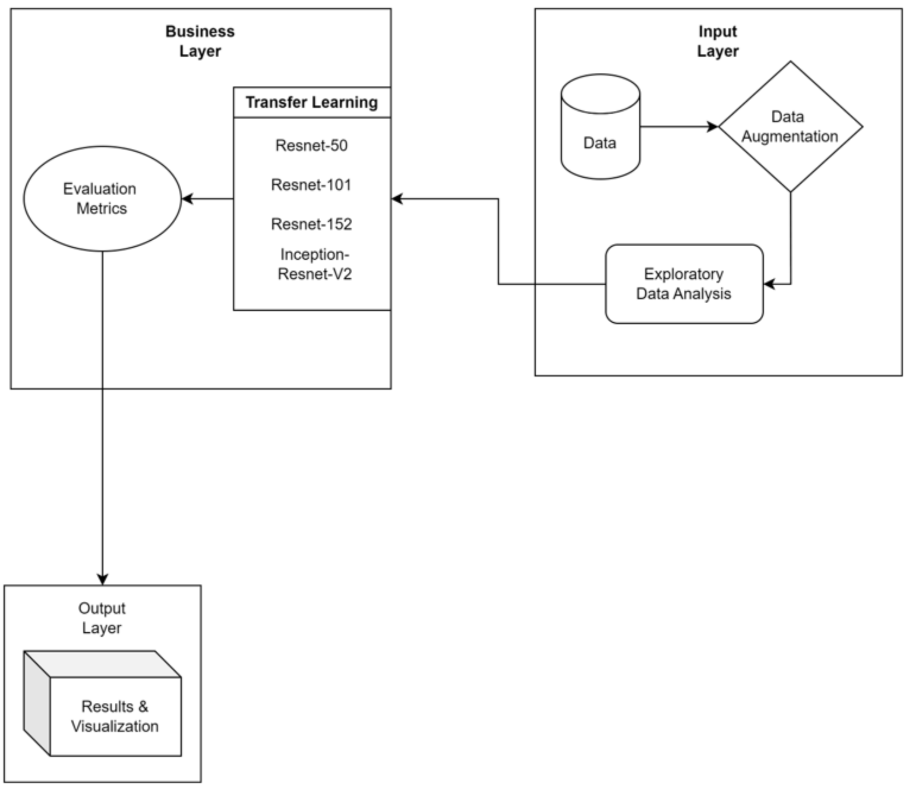
- F1- Score

  F1- Score is the most important evaluation metric of all because the precision and recall are combined in it to balance the overall positive classes.

  F1-Score = 2 * (Precision * Recall / Precision + Recall)

4 Design Specification

The design architecture of this research has three sections Input Layer, Business Layer and the Output Layer.



(Fig:4) Process Design Architecture

Input Layer: The first layer consists of data collection, Data Pre-processing and Exploratory Data Analysis. The dataset is taken from the open-source website Kaggle where it contains 5856 x-ray images of patient lungs with pneumonia and not. The Image dataset is Pre-processed, in this case the images are augmented with various augmentation techniques like rotating, zooming and flipping. Then the augmented data is visualized on the

class basis for better understanding.
Business Layer: Transfer Learning is the process of using pre-built models rather than building a convolutional neural network from the scratch. In this phase the pre-processed data is fitted into the pre-built models such as the type of residual networks. The models are evaluated using different evaluation metrics such as accuracy,loss and F1-Score.
Output Layer: The Output layer contains the results and visualization of various graphs of the overall research which could be used in business by doctor's to predict whether a person is affected by pneumonia or not, So that the doctor could advice the person to take effective treatment.

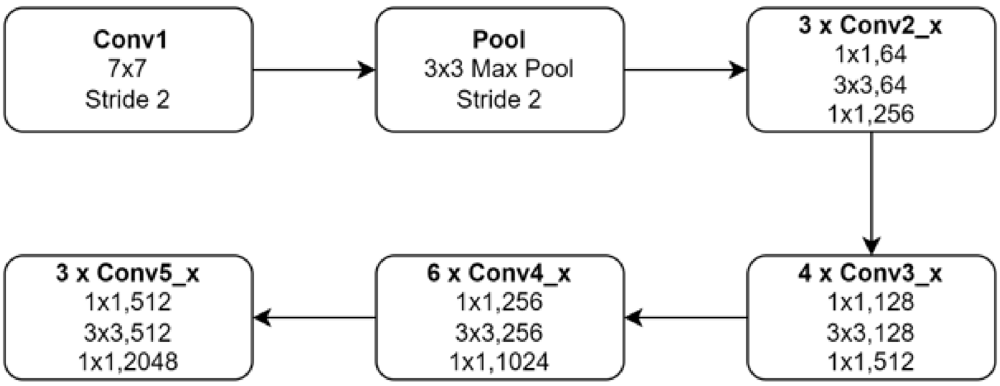
5 Implementation

Among the different types of Resnet models suchs as 18,34,50,101,152 and InceptionResnet, a few of the Resnet models namely 50,101,152 and Inception-Resnet of version 2 are implemented to detect the pneumonia disease using the x-ray images of patient lungs.

The architecture of the four Resnet models with diagrammatic representation are explained and discussed with their difference among them.

5.1 Resnet-50

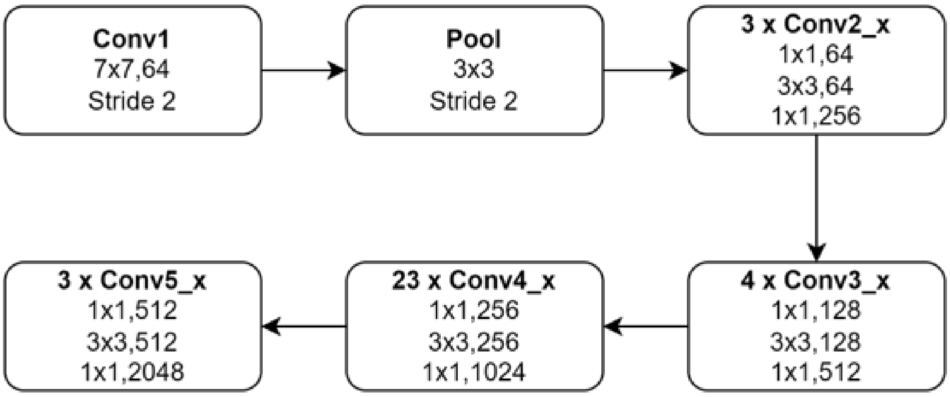
The first residual model consists of 50 layers known as the resnet-50 which is one of the most common model. The first two layers are common for all the residual networks because of their input size, it has 7x7 filter with a stride of 2 followed by a pooling layer (Max Pooling with 3x3) followed by a convolutional layer of 1x1 filter and 3x3 filter. Each convolutional layer's first set uses skip connections. In that case, so that the second round of the layer could get the original input. All these models are followed by a flatten and dense layer at the end.



(Fig:5) Resnet-50 Architecture

5.2 Resnet-101

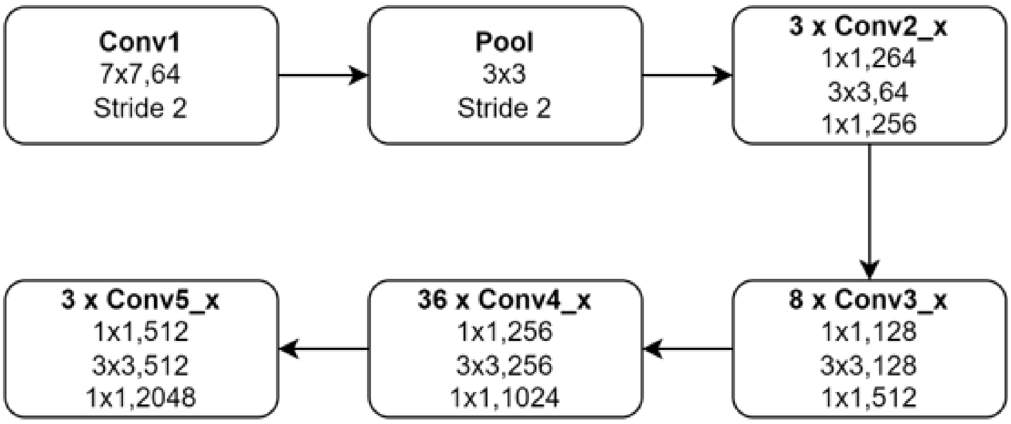
Resnet-101 consists of the same four layers as of Resnet-50, but the wheeling number of convolutional layer differs. The fourth convolutional layer runs for 23 times whereas in the Resnet-50 it ran for 6 times followed by fifth convolutional layer with the same number of filters in it.



(Fig:6) Resnet-101 Architecture

5.3 Resnet-152

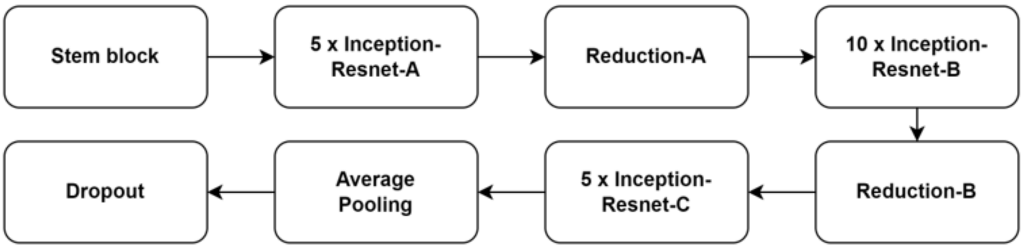
Resnet-152 model consists of 152 layers, it has the first three layers similar with the resnet-101 whereas in the third convolutional layer runs 8 times followed by the fourth layer for 36 wheelings with the same number of runs in the last layer. Eventhough the filters are the same in all models, the number of times the layer is executed differs from one model to another.



(Fig:7) Resnet-152 Architecture

5.4 Inception-Resnet-V2

Inception-Resnet-v2 ia an hybrid model which is a formulated model inspired by a combination of Residual network and Inception model with 164 layers. It has residual connections with multiple sized convolutional layers. The degradation could be avoided with the help of residual connections in the model.

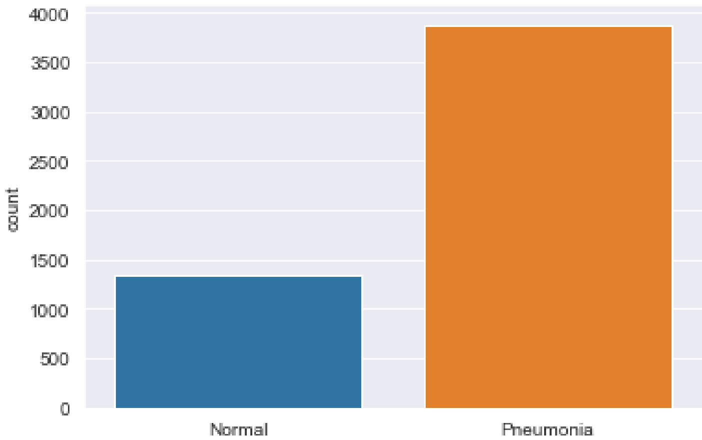


(Fig:8) Inception-Resnet-V2 Architecture

A flatten function and dense function are applied on top of each residual network model.

6 Evaluation and Results

Evaluation metrics is the most important part of an research, where it defines the efficiency of the model. The various evaluation metrics used in this research and their results are discussed. In this research the train dataset is plotted into a bar graph which distinguishes the two classes normal and pneumonia and then augmented.

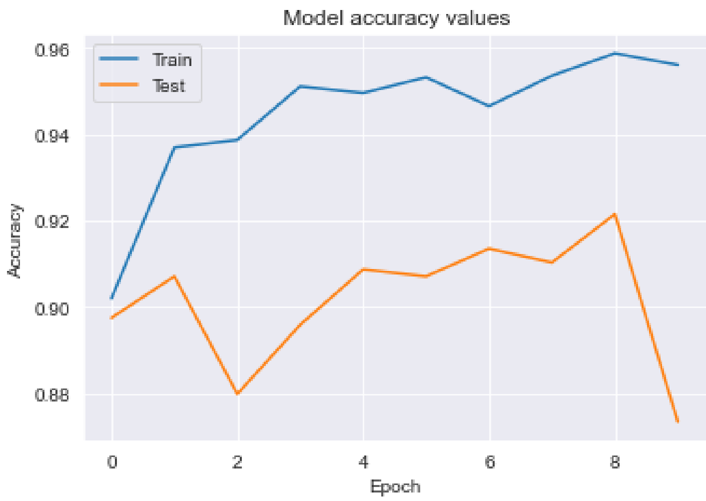


(Fig:9) Distribution of Image Classes

The four models are evaluated on various evaluation metrics namely accuracy, Validation accuracy, Loss of data on both train and test data, Confusion Matrix, Precision, Recall and F1-Score. The models are trained with minimum number of epochs (10) as an experiment which could be changed in the future work with different number of epochs.

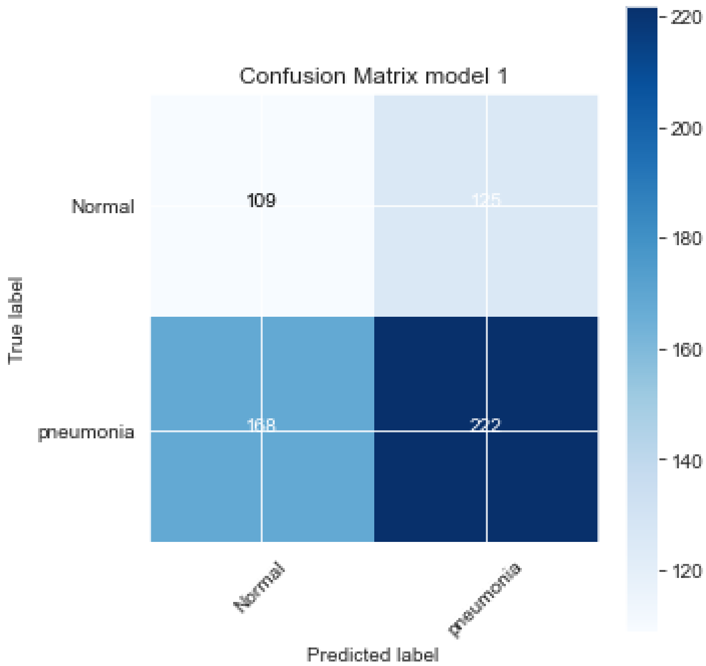
6.1 Resnet-50

Resnet-50 is the most common and plain residual network. The model gave out an accuraccy of 95 percent on train dataset and 87 percentage on the validation with an loss of 0.17 on train and 0.58 on test dataset. A graph has been plotted on the accuracy of train and validation on different number of epochs.



(Fig:10) Resnet-50 Accuracy Graph

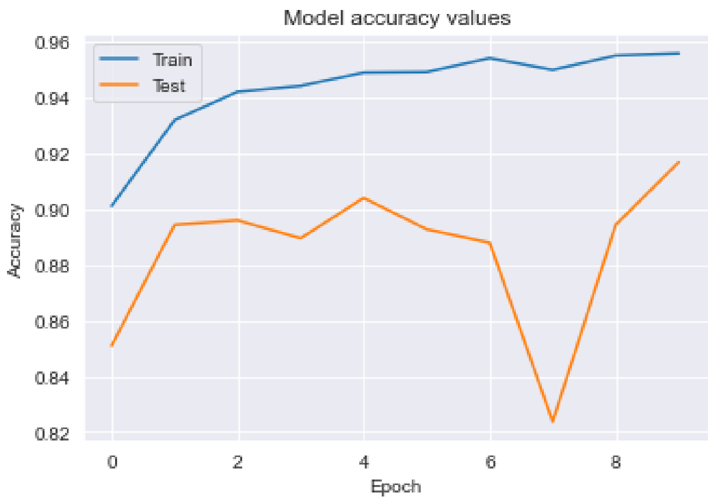
A confusion matrix with the values of true positive, false positive, false negative and true negative are plotted from which a F1-Score of 54 percent is obtained along with an precision and recall value of 55 and 53 percentage on weighted accuracy.



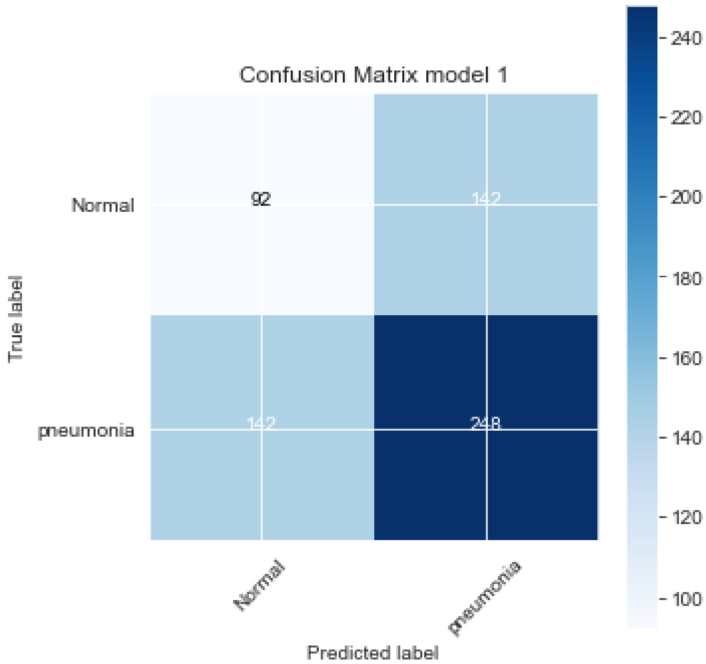
(Fig:11) Resnet-50 Confusion Matrix

6.2 Resnet-101

The second model Resnet-101 obtained an accuracy of 95 percent and 91 percentage on the test dataset with an loss of 0.16 on train and 0.44 on the test dataset. A graph has plotted on the train and test accuracy along with the number of epochs.



(Fig:12) Resnet-101 Accuracy Graph

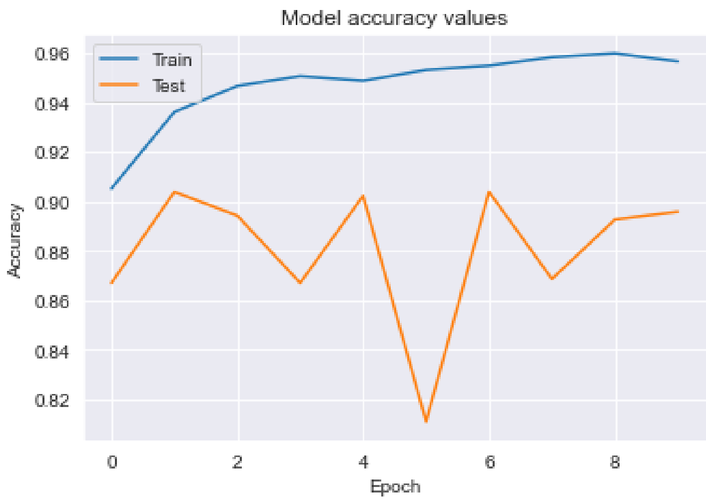


(Fig:13) Resnet-101 Confusion Matrix

From the above confusion matrix the precision and recall value of 54 percent are obtained along with an F1-Score of 54 percent is acquired.

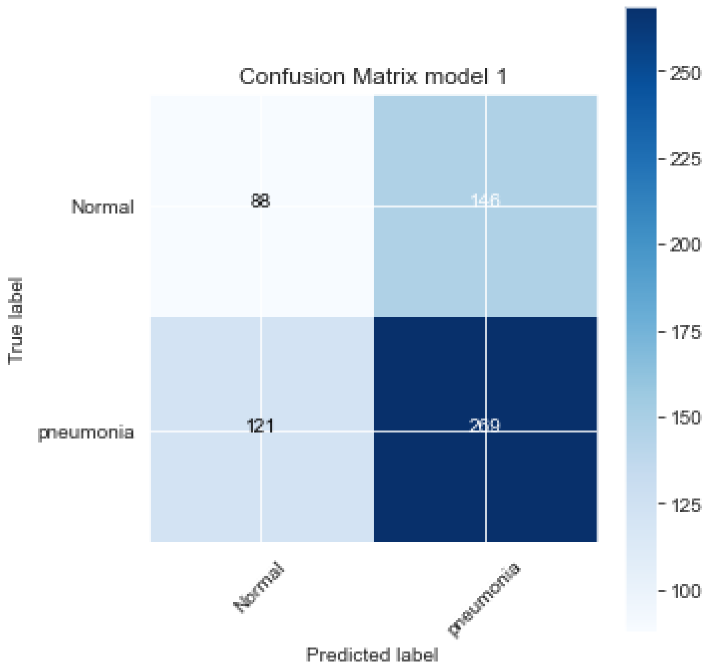
6.3 Resnet-152

Resnet-152 is the last solid residual network with more number of layers which gained an accuracy of 95 percent with an loss of 0.16 on the training dataset,whereas in the test data it secured an 89 percent with a loss of 0.43 percentage.



(Fig:14) Resnet-152 Accuracy Graph

The above diagram shows the accuracy of train and test data over the various epochs. A confusion matrix as well plotted for the resnet-152 for evaluation.

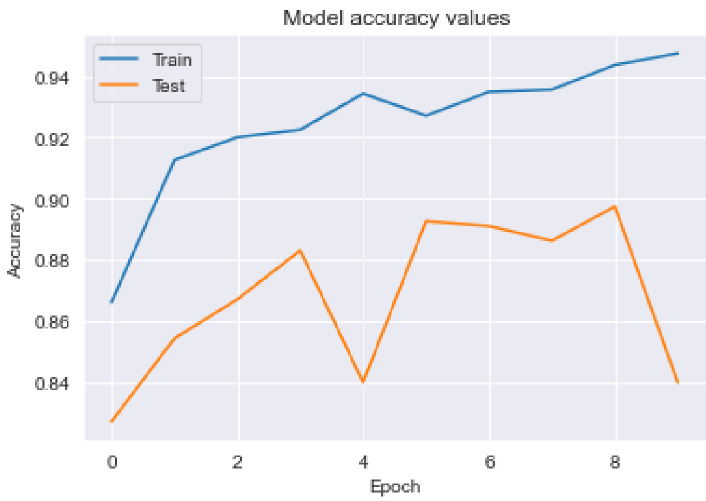


(Fig:15) Resnet-151 Confusion Matrix

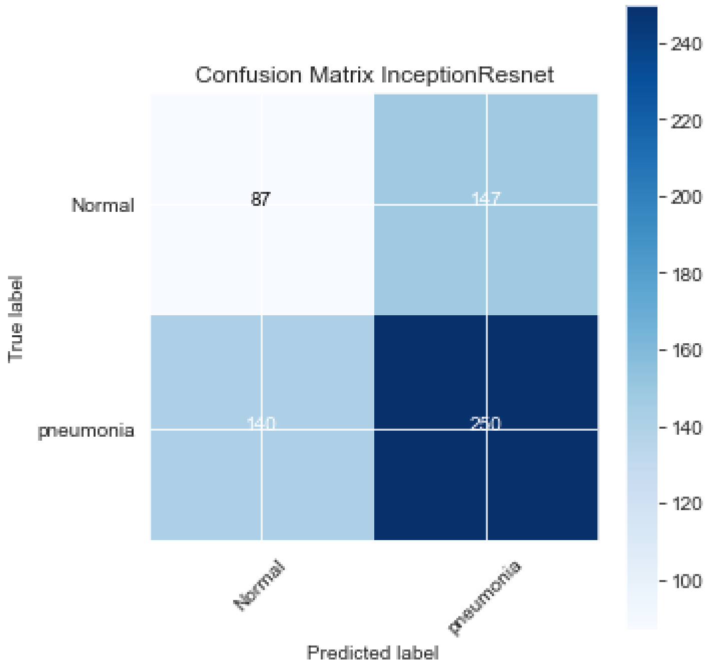
With the help of values from the above confusion matrix a precision score of 56 percentage along with a recall value of 57 percentage and a F1-score of 57 is obtained in this model.

6.4 Inception-Resnet-V2

Inception-resnet-v2 is an hybrid model of inception and residual networks to sight the difference between a pure residual model with an hybrid residual model.The model establishes an accuracy of 94 percent on train and 83 on test data with a loss of 0.14 and 0.42 percentage.



(Fig:16) Inception-Resnet Accuracy Graph

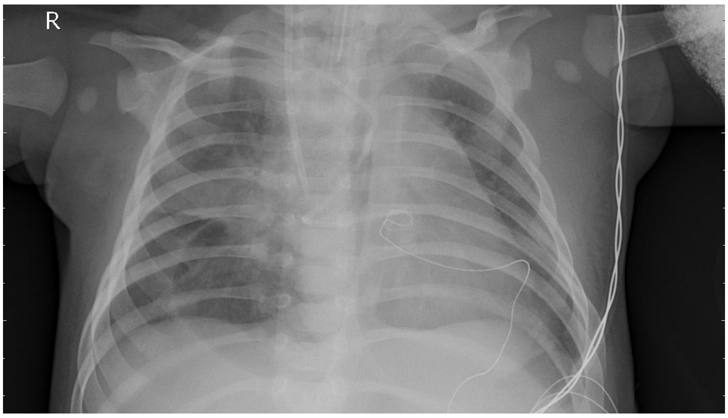


(Fig:17) Inception-Resnet Confusion Matrix

From the above confusion matrix, precision and recall score of 54 percent is calculated and a F1-score of 54 percentage is calculated.

7 Discussion

The models built on this research produce a very good accuracy with the minimum loss of data using categorical cross-entropy, but it does not produce a very good F1-Score. When the Images which are wrongly classified are checked most of the images contain noise in that such as earphones and wires on the x-ray images. The below image shows a example of noise on the dataset. The models could predict the disease but even with noise on the image could result in false value.



(Fig:18) Sample Image with Noise

The disease pneumonia has been detected using the x- ray images using various resnet models, even though the layers are different all models almost produce the same result with slight difference. The limitation of this research is that the models could not distinguish the type of pneumonia whether it is viral pneumonia or bacterial pneumonia. The objectives of this research are satisfied by detecting pneumonia with new deep learning models with time and cost efficient.

8 Conclusion and Future Work

This study states the importance of deep learning for detecting the presence of pneumonia using x-ray images with different type of residual network models. In this research four residual network models are implemented with different number of layers, to see the difference among them. Residual networks are specifically chosen because for their ability to skip connections, so that the model could perform with the true data and also to solve gradient descent. The dataset contains x-ray images of patients lungs which have been augmented and fitted on the four resnet models with a addition of flatten and dense layer on top of every model with weights of imagenet. Among the four models Resnet-50 has the less training time but Resnet-152 outperforms other models by a minimum difference with a maximum F1- score. Even though the accuracy of all the models are almost the same, a slight increase in F1-score makes the Resnet-152 the better model.

In future more models like Resnet-34, Resnet-110 and Resnet-1202 could be tested on the same dataset. In this research the dataset used has been already splitted with imbalanced classes which resulted in poor F1-score. In the future these models could be tested on a dataset with balanced classes with new augmentation techniques and with more number of epochs.

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