Annexure-1 (A typical Specimen of Title Page)

By using Chest X-ray performing pneumonia detection

A Project Work Synopsis

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Artificial Intelligence and Machine learning

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Abstract

Pneumonia is a life-threatening disease, which occurs in the lungs caused by either bacterial or viral infection. It can be life-endangering if not acted upon at the right time and thus the early diagnosis of pneumonia is vital. Keeping that in mind we have worked on developing an algorithm that can detect pneumonia from chest X-rays at a level exceeding practicing radiologists. Our algorithm, PnEXRay, is a 121 layer convolution neural network trained on ChestX-ray14 data set, currently the largest publicly available; chest X-ray data set, containing more than 100,000 frontal view X-ray images with 14 diseases. We concluded that PnEXRay exceeds average radiologist performance on the F1 metric.We extend PnEXRay to detect all 14 diseases in ChestX-ray 14 and achieves state of the art results on all 14 diseases. There are three schemes of classifications: normal vs. pneumonia, bacterial vs. viral pneumonia, and normal, bacterial, and viral pneumonia. The classification accuracy of normal and pneumonia images, bacterial and viral pneumonia images, and normal, bacterial, and viral pneumonia were 98%, 95%, and 93.3%, respectively. This is the highest accuracy, in any scheme, of the accuracies reported in the literature. Therefore, the proposed study can be useful in more quickly diagnosing pneumonia by the radiologist and can help in the fast airport screening of pneumonia patients.

1 INTRODUCTION

1.1Problem Definition-

More than 1 million adults are hospitalized with pneumonia and around 50,000 die from the disease every year in the US alone. Pneumonia is considered the greatest cause of child fatalities all over the world. Pneumonia is a lung infection, which can be caused by either bacteria or viruses. Luckily, this bacterial or viral infectious disease can be well treated by antibiotics and antivirals drugs. Nevertheless, faster diagnosis of viral or bacterial pneumonia and the consequent application of correct medication can help significantly to prevent deterioration of a patient's condition, which eventually leads to death. ChestX-rays are currently the best available method for diagnosing pneumonia, playing a crucial role in clinical care and epidemiological studies. However, detecting pneumonia in ChestX-rays is a challenging task that relies on the availability of expert radiologists. In this work, we present a model that can automatically detect pneumonia from ChestX-rays at a level exceeding practicing radiologists.

Currently, many biomedical complications (e.g., brain tumor detection, breast cancer detection, etc.) are using Artificial Intelligence (AI)-based solutions. Among the deep learning techniques, convolutional neural networks (CNNs) have shown great promise in image classification and therefore widely adopted by the research community. Deep Learning Machine learning techniques on chest X-rays are gaining popularity as they can be easily used with low-cost imaging techniques and there is an abundance of data available for training different machine-learning models. Several research groups have reported the use of deep machine learning algorithms in the detection of pneumonia; however, only one article has reported the classification of bacterial and viral pneumonia.

The highest accuracy reported in the above-mentioned literatures in classifying the normal vs. pneumonia patients and bacterial vs. viral pneumonia using X-ray images using deep learning algorithms was 96.84% and 93.6%, respectively. Therefore, there is significant room for improving the result either by using different deep learning algorithms or modifying the existing outperforming algorithms or combining several outperforming algorithms as an ensemble model to produce a better classification accuracy, particularly in classifying viral and bacterial pneumonia.

1.2 Project Overview-

Pneumonia, an interstitial lung disease. Is the Pneumonia, an interstitial lung disease. Is the leading cause of death in children under the age of five, It accounted for 16% of the deaths. With the growing technological advancements we have in this day and age, it is possible to use tools based on deep learning frameworks to detect pneumonia based on chest x-ray images. The challenge here would be to aid the diagnosis process which allows for expedited treatment and better clinical outcomes. To obtain the best results, a certain number of combinations of convolution layers, dense layers, dropouts and learning rates have to be trained by evaluating the models after each execution. . Initially, simple models with one convolution layer were trained on the dataset, and thereafter, the complexities were increased to get the model that not only achieved desired accuracies but also outperformed other models in terms of recall and F1 score.

1.3 Software Specification

The minimum software requirements that will be used in making this are:

1. Windows or linux operating system
2. Python3 should installed on the system
3. These libraries should also be installed: Tensorflow, Keras, Numpy, OpenCV, Flask

1.4 Hardware Specification

1. Dual Core CPU
2. Minimum 256 MB RAM
3. Minimum 200 MB storage

2 LITERATURE REVIEW

2.1 Literature Review Summary

Table 2.1: Literature review summary

Authors	Method Used	Dataset	Advantages	Challenges
Abiyev et al.	CNN, CpNN, and BpNN	Chest X-rays	Accuracy= 92.4%, CpNN(80.04%), BPNN(89.57%)	Accuracy needs improvement, CNN converges slower than CPNN
Stephan et al.	CNN with four convolution layers.	Pediatric chest X-rays	Less computationally complex model, accuracy=93.7%	Non-standard division of dataset, no performance metrics other than accuracy were evaluated.

2.2 Proposed System- As previously mentioned, pneumonia affects a large number of individuals, especially children, mostly in developing and underdeveloped countries characterized by risk factors such as overcrowding, poor hygienic conditions, and malnutrition, coupled with the unavailability of appropriate medical facilities. Early diagnosis of pneumonia is crucial to cure the disease completely. Examination of X-ray scans is the most common means of diagnosis, but it depends on the interpretative ability of the radiologist and frequently is not agreed upon by the radiologists. Thus, an automatic system with generalizing capability is required to diagnose the disease. To the best of our knowledge, most previous methods in the literature focused on developing a single CNN model for the classification of pneumonia cases, and the use of the ensemble learning paradigm in this classification task has not been explored. After analyzing and reading various datasets available on various platforms and websites, pneumonia dataset was found to be best fit for performing on and making a model to detect it using image dataset of chest X-rays of patients. World health organization (WHO) states that the pneumonia is the leading reason for the child dearth in the world. It had killed approximately 1.2 million children under the age of five. And south Asia is leading the table. South Asian countries like Indian Pakistan, Bangladesh, Sri Lanka, Indonesia etc. have the most no. children having pneumonia disease. Not only is this death rate of pneumonia greater than death rate of other dangerous disease like AIDS, malaria and tuberculosis combined. Pneumonia is one of the gravest illnesses among children younger than five years of age. This was motivation enough to work on this dataset and produce a model with accuracy good enough to successfully detect pneumonia by reading chest X-rays While examining for pneumonia in the patient’s X-ray, the radiologist looks in it for spots, specifically white ones, within the lungs termed as “infiltrates” which are helpful in identifying the infection. Pneumonia chest x-ray can be observed in TB, severe case of bronchitis as well. Complete Blood Count (CBC), Chest Computed Tomography (CT) and sputum test etc. are further conducted to reach a conclusion about the infection. Therefore, in this attempt to solve the problem we have only tried to detect whether a chest x-ray conclude that a person is ill with pneumonia or normal patients and do so by searching for any cloudy pattern in the X-ray. Conclusive detection will therefore, depend on pathological tests only. Today many diseases are detected using Artificial Intelligence based solution. Some of these diseases are breast cancer, brain tumor etc. based solutions. This Artificial Intelligence based detection by Convolutional Neural Network have played a great part and shown great promises in classification and this AI based classification in trusted by doctors all over the world. When we talk about low-cost imaging methods and easy use, Deep and machine learning methods are gaining popularity when it comes to examining chest X-rays. Also, the fact that there is ample of data available for training of various machine learning models. Among all the papers studied by us, the highest accuracy was obtained was 98%. Thus, we chose CNN for operating on our dataset and took the help of this deep learning approach to obtain accuracy better than other models using other deep learning approaches

3. PROBLEM FORMULATION

The ensemble learning model helps incorporate the discriminative information of all its constituent models, and thus, its predictions are superior to those of any of its constituent base learners. Weighted average ensembling is a powerful classifier fusion mechanism. However, the choice of the weights to be allocated to the respective base learners plays a pivotal role in ensuring the success of the ensemble. Most approaches in the literature set the weights experimentally or based solely on the accuracy of the classifier. However, this may not be a good measure when a class imbalance exists in the dataset. The use of other evaluation measures, such as precision, recall (sensitivity), f1-score, and AUC, may provide relatively robust information for determining the priority of the base learners. To this end, in this study, we devised a novel strategy for weight allocation, which is explained in the following.

First, the probability scores obtained during the training phase by the base learners are utilized to calculate the weights assigned to each base learner using the proposed strategy. These generated weights are used in the formation of an ensemble trained on the test set. This strategy is implemented to ensure that the test set remains independent for predictions. The predictions of the i^{th} model ($\hat{y}^{i}$) are generated and compared with the true labels (y) to generate the corresponding precision score ($pre^{(i)}$), recall score ($rec^{(i)}$), f1-score ($f1^{(i)}$), and AUC score ($AUC^{(i)}$). Assume that this forms an array $A^{(i)} = \{pre^{(i)}, rec^{(i)}, f1^{(i)}, AUC^{(i)}\}$. The weight ($w^{(i)}$) assigned to each classifier is then computed using the hyperbolic tangent function. The range of the hyperbolic tangent function is [0, 0.762] because x represents an evaluation metric, the value of which is in the range [0, 1]. It monotonically increases in this range; thus, if the value of a metric x is high, the *tanh* function rewards it by assigning to it a high priority; otherwise, the function penalizes it.

$$w^{(i)}=\sum_{x\in A^{(i)}}\tanh(x)=\sum_{x\in A^{(i)}}\frac{e^{x}-e^{-x}}{e^{x}+e^{-x}}$$

These weights ($w^{(i)}$) computed are multiplied by the decision scores of the corresponding base learners to compute the weighted average probability ensemble, where the probability array (for a binary class dataset) of the j^{th} test sample by the i^{th} base classifier is $p^{(i)}_{j}=\{a,1-a\}$, where $a \leq 1$ and the ensemble probability for the sample is $ensemble\_prob_j = \{b, 1 - b\}$.

$$ensemble\_prob_j=\frac{\sum_i w^{(i)}\times p^{(i)}_{j}}{\sum_i w^{(i)}}$$

Finally, the class predicted by the ensemble is compute, where $prediction_j$ denotes the predicted class of the sample.

$$prediction_j=\operatorname{argmax}(ensemble\_prob_j)$$

4 OBJECTIVES

The proposed work is aimed to carry out work leading to the development of an approach for detecting pneumonia using chest X-rays. The proposed aim will be achieved by dividing the work into following objectives:

1. First developing the deep learning model to detect pneumonia using the convolutional neural networks. The main libraries used here are tensorflow and keras.
2. Now, second part is making the model available through a website which is done using flask which is a web framework for python.
3. At last, the model is deployed and the website is created for use.
4. Now, html and css can be used to make the website presentable and look good.

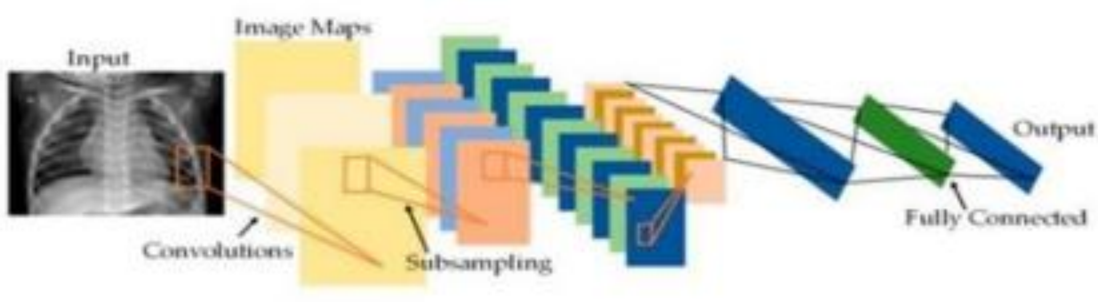
3. BACKGROUND INFORMATION ON MACHINE LEARNING METHODS

- Convolutional Neural Network or CNN, due to its better than ever efficiency in Image classification, is becoming quite popular now-a- days. Features such as spatial and temporal in an image are easily extracted using CNN. Each layer has some specific weight as CNN use weight- sharing technique as it reduces the computation efforts. Architecture wise, Convolutional Neural Network are simply forward feed artificial neural Network (ANN) with only two limitations. To reduce the total number of parameters of the model, firstly the weights should be shared and secondly neurons which are in the same layers are connected to local paths only. There are three basic building blocks in CNN to preserve the spatial structure:

  • A convolution layer

  • A max-pooling layer to reduce the Dimension of the map

  • A fully connected layer to classify the between the kinds



The architectural explanation of CNN

2

- Normalization has been a full of life research field of deep learning normalization is used to reduce the training time by a lot of factors, allow us to show a number of the advantages of using Normalization.

  • Sometimes some features have a very high value as compared to the feature surrounding it, so in this process we normalize each and every feature is maintained. By doing so, we're making our network unbiased.

  • Normalization decreases the internal covariate shift. Covariate shift is the change within the distribution of activation network .and because of the alteration in the network parameters during training of the model. To boost the training, we need to scale back the Internal Covariate Shift

  • As stated in point no. 1 normalization maintains the features but the sharp feature is lost because of normalization

  • Normalization paces up the Optimization as normalization do not allow weights to explode and it also restrict them to a specific range

- Normalization also helps CNN in regularization which is one unintended benefit of it (only slightly, not significantly though) .The normalization technique used in our model was Batch Normalization.

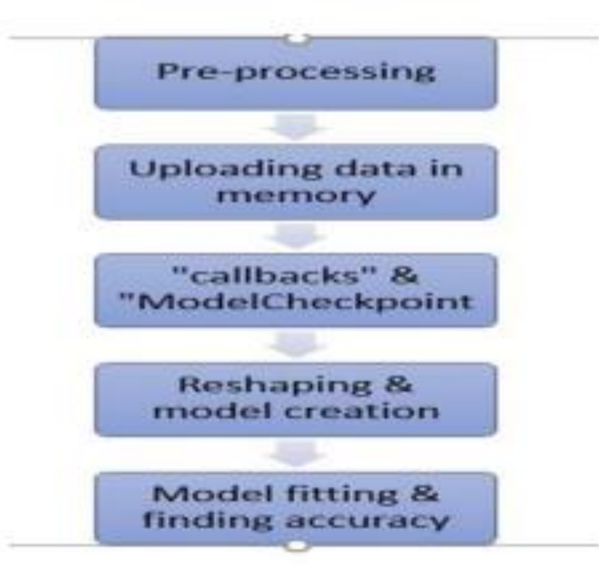
- Batch normalization is one of the many methods that normalize activations in a network across the mini-batch of definite size. For each feature, batch normalization computes the mean and variance of that feature in the mini batch. It then subtracts the mean and divides the feature by its mini-batch standard deviation.
- Pooling is one the most common feature imbibed in the Convolutional neural Network. The main idea behind the pooling layer is to “accumulate of collect” feature of the normalized feature map created by convoluting a filter over the picture. The Primary job is to continually decrease the featured map’s spatial size and decrease the number computation efforts of the network. Max pooling is the most used type of pooling.

4. RESEARCH OBJECTIVE

Pneumonia is form of a respiratory infection that affects the lungs. In these acute respiratory diseases, human lungs which are made up of small sacs called alveoli which in air in normal and healthy people but in pneumonia these alveoli get filled with fluid or "pus” one of the major step of phenomena detection and treatment is getting the chest X-ray of the (CXR). Chest X-ray is a major tool in treating pneumonia, as well as many decisions taken by doctor are dependent on the chest X-ray. Our project is about detection of Pneumonia by chest X-ray using Convolutional Neural Network. This paper written by us is an efficient approach towards classifying chest X- rays into pneumonia and no pneumonia X-rays. We have taken this approach as the most used radiography method produces errors. So, we have used CNN and batch normalization from keras to develop this model, and calculated accuracy using confusion matrix. We were successful in doing so with the help of “Python” and “OpenCV”, both of which are freely available and are open source tools and can be used by anyone. Pneumonia day, states that by the year 2030, 11 million children who are under the age of 5 year.

5 METHODOLOGY

The methodology and approach we've used has been describes step by step ahead. The task has been performed as per the following step. We have preprocessed the data and all the X-ray images were cropped to the ideal dimensions for computational needs. Next, we uploaded the data in the memory. Then we created a callbacks function and model checkpoint. Next, we reshaped the data and created the model through CNN. And last we did model fitting and found the accuracy and value loss using confusion matrix**.**



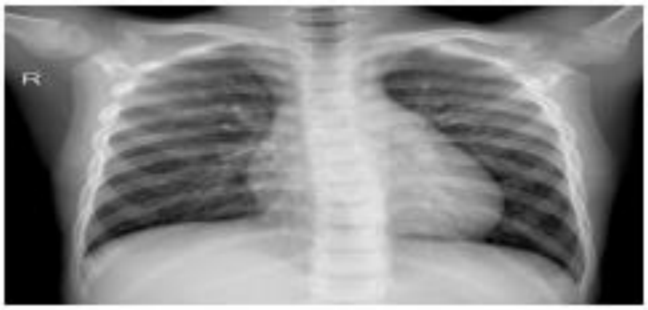
Flowchart of methodology

1. Pre-processing

In this we have resized the images for performing efficient operation on them. The images were resized to a compatible size for better computation. We also created a function in which pneumonia file in training dataset is given label = 0 and normal label = 1, else = 2. Two arrays, 'X' and 'Y' are created where 'X' stores pre-processed (resized image) data and 'Y' stores the label which is again stored back in the file we use the function 'resize' of OpenCV, and uploading the images in new h5py file whose main function is to store the data in binary format, means images of chest X-ray are converted to array of numbers.

2. Uploading data in memory

Now, as the data has been pre-processed, we considered uploading it in the memory. We create a function to do so, it loads the training dataset and also the test dataset along with their labels. Afterwards, the shape of test and train datasets is obtained and the X-rays are displayed of both, with pneumonia and without pneumonia using "matplotlib".

1 

Sample Chest X-ray

```
[[[[0.2745098  0.2745098  0.2745098  ... 0.06603
399 0.06603399
   0.06603399]
  [0.1731817  0.1731817  0.1731817  ... 0.01191
634 0.01191634
   0.01191634]......................................
.........................................................
.........................................................
[0.        0.        0.        ... 0.77254902 0.7725490
2
```

Converted X-ray in array

3. Callbacks and model checkpoint

We have imported "ModelCheckpoint" from the "callbacks" library of "keras". We have done so as to reduce learning rate timely after monitoring a quantity. Model Checkpoint call back is utilised in addition with the training using model.fit() function to save some the model or weights (in checkpoint file) at some interval, model/weights are hence loaded afterwards to continue with the previously saved model making checkpoints which helps in timely check and save the best model performance till last and also avoid further validation accuracy drop due to over fitting.

4. Reshaping and model creation

Now we had imported various models from “keras library” for creating our model according to the dataset. We reshaped the “X_train” and ”X_test” with “.reshape(5216,3,150,150)” and “.reshape(624,3,150,150)” respectively.

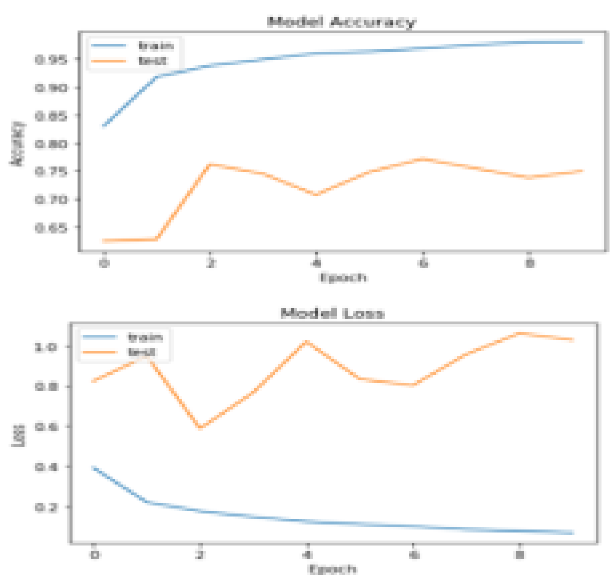
5. Model fitting and finding the accuracy

Next and final step in the completion of the project is fitting the training data set in the model using .fit() function in which the arguments are X_train and y_train and callback function to reduce the learning rate and the value of epochs (in our project the value epochs is set to be 10). As now our model is trained and fit to go and final readings we got after fitting the dataset are:

- val_accuracy is found to be 0.8410
- val_loss is found to be 0.8395
- Accuracy is found to be 0.9806
- Loss is found to be 0.0742 (after 10 epochs)

6. Performance and Result

Performance of a CNN model over the testing data set is calculate after the completion of the training of the model and the performance is calculated in the following six metrics: accuracy, precision (PPV), sensitivity or recall, F1 score, the area under the curve (AUC), and specificity. Figure given below tells the formulae to calculate the above metrics:



Graph between Accuracy and Loss against epochs

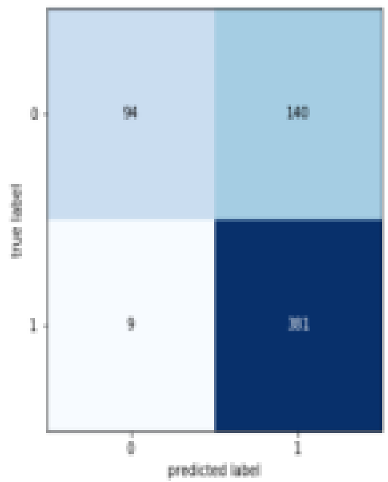
False negative are those X-rays which are normal x-rays and have been detected wrongly by the machine, false positive are those X-rays which are normal x-rays and have been detected correctly by the machine, True Negative are those cases which are pneumonia X-rays but have been detected as normal cases but the model and true positive are those case which are pneumonia cases and have been detected correctly by the machine. Here is an example of this confusion table:

	Predicted: NO	Predicted: YES
Actual: NO	TN = ??	FP = ??
Actual: YES	FN = ??	TP = ??

Example of a confusion table

The value we got after the successful compilation of our model is given in the figure below:

```
In [35]:
CM = confusion_matrix(y_true, pred)
from mlxtend.plotting import plot_confusion_matrix
fig, ax = plot_confusion_matrix(conf_mat=CM ,  figsize=(5, 5))
plt.show()
```



Confusion matrix of the model

Here 0 means non-Pneumonia and 1 means Pneumonia.

7. Conclusion and Future Scope

Detection of diseases with the assistance of computers from various Machine and Deep learning techniques are very beneficial in such places where there is shortage of people who are skilled in techniques like radiology. Especially in south Asian countries and African countries where of 60% - 70% people live in rural places. Such tool are very low cost and instrument requirement is low hence it very easy to deploy in rural areas. And, additionally these tools will be very helpful in automatically differentiating between who need urgent medical care and who can be made to wait. Out project successfully provides with a CNN based approach for detection of pneumonia automatically. Detection of diseases with the assistance of computers from various Machine and Deep learning techniques are very beneficial in such places where there is shortage of people who are skilled in techniques like radiology. Especially in south Asian countries and African countries where of 60% - 70% people live in rural places. Such tool are very low cost and instrument requirement is low hence it very easy to deploy in rural areas. And, additionally these tools will be very helpful in automatically differentiating between who need urgent medical care and who can be made to wait. Out project successfully provides with a CNN based approach for detection of pneumonia automatically.

Conclusion Stats	
Validation Accuracy	0.8410
Validation Loss	0.8395
Accuracy	0.9806
Loss	0.0742

Final Results

7. TENTATIVE CHAPTER PLAN FOR THE PROPOSED WORK

CHAPTER 1: INTRODUCTION

This chapter will cover the overview and blueprint of the project.

CHAPTER 2: LITERATURE REVIEW

This chapter include the literature available for the proposed implementation of the project ideas. The findings of the researchers will be highlighted which will become basis of current implementation.

CHAPTER 2: BACKGROUND OF PROPOSED METHOD

This chapter will provide introduction to the concepts which are necessary to understand the proposed system.

CHAPTER 4: METHODOLOGY

This chapter will cover the technical details of the proposed approach.

CHAPTER 5: EXPERIMENTAL SETUP

This chapter will provide information about the subject system and tools used for evaluation of proposed method. Along with this the implementation detail of the networks will be discussed.

CHAPTER 6: RESULTS AND DISCUSSION

The result of proposed technique will be discussed in this chapter.

CHAPTER 7: CONCLUSION AND FUTURE SCOPE

The major finding of the work will be presented in this chapter. Also directions for extending the current study will be discussed.

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