Predicting Pneumonia using CNN

MINI PROJECT- REPORT

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ABSTRACT :

Pneumonia is an inhaling infection/lung illness occurring due to a number of bacteria, fungi, or viruses; it is more frequent in developing and impoverished countries because of more pollution, unsanitary living conditions, and overpopulation, as well as limited medical infrastructure. The fluids that fill the lung generate pleural effusion, which causes breathing issues. Early identification of pneumonia is critical for ensuring curative therapy and increasing the chances of survival. In the medical field, generally, an X-ray scan of the chest is used to detect pneumonia. Detection of pneumonic condition via chest X-rays is a tedious task that can be subject to variation. Here, we have tried to develop a web-based diagnosis system to automate pneumonia detection using images of the chest X-ray.

1. INTRODUCTION:

Pneumonia is an acute respiratory lung infection that is caused by bacteria , viruses or fungi which causes inflammation of the small sacs in our lungs called the alveoli, used to full up air when we breathe in air. When this inflammation is caused, these small sacs get filled with pus and fluid thus giving a sensation of pain while breathing and also limits the oxygen intake.

"Pneumonia is responsible for more than 15% deaths among the children under the age of five and is the single largest cause"[12]. According to WHO data, "deaths relating to pneumonia in children under 5 years of age accounts for 8,08,694, and is a commonly found disease in South-Asia and Sub-Saharan regions" [12]. The commonly found symptoms found in children under the age of 5 are cough and breathing problems may be accompanied with fever.

Many disorders have been aided by the advancement of technology in the medical industry. Artificial Intelligence has helped in the early detection of diseases as well as catering to a bigger set of patients. These techniques could be used to automate detection processes and to improve efficiency and accuracy in the process. Our dataset must have all features as well as sufficient photos for training and assessing the model.

Deep learning is a powerful artificial intelligence method that can help solve a variety of difficult computer vision problems [13,14]. For diverse image categorization issues, deep learning models, notably convolutional neural networks (CNNs). However, such models work best when given a significant amount of data. Such a large volume of labeled data is difficult to obtain for biomedical image classification problems since it takes experienced doctors to identify each image.

2. LITERATURE SURVEY AND MOTIVATION:

Detection Of Pneumonia through chest X-rays has been a long-standing issue with the main constraint being a lack of data available publicly. Traditional techniques of machine learning have been thoroughly investigated. Several studies employing deep learning to diagnose pneumonia and other respiratory disorders have been published in the last few years. The use of stochastic gradient descent, transfer learning, and convolutional neural networks, for the pneumonic diagnosis is described in this paper.

Unlike machine learning techniques, which involve the extraction and selection of handmade features for segmentation or classification, deep learning-based methods accomplish end-to-end classification by automatically extracting and classifying useful and relevant characteristics from the input data. Convolutional Neural Networks (CNNs) are preferred for image classification because they automatically extract translationally invariant features by convolutioning the input picture and filters. Researchers frequently use CNNs because they are translationally invariant and perform better than standard image processing algorithms in picture classification tasks or machine learning.

Simple CNN architectures were developed by Sharma and others[1] and Stephen and others[2] for the classification of pneumonic chest X-ray images. To compensate with the lack of the data available, they(in [19 &20]) employed data augmentation. On the dataset provided by Kermany and others [3], hereafter referred to as the Kermany dataset, Sharma and others obtained a 90.68% accuracy rate and Stephen and others obtained a 93.73% accuracy rate. However, data augmentation only supplies a limited quantity of new data for the Convolutional Neural Networks to learn from, and so may not considerably improve their performance.

Rajpurkar, and others [4] (2017) developed an algorithm for the detection of pneumonia from chest X-rays at a level higher than a practicing radiologist using 121 layers CNNs using the X-ray of chest of 14 datasets. To improve their model, they may consider the patient's history and lateral radiographs.

Transfer learning, in which knowledge learned from a bigger dataset is applied to fine-tune the model on a current smaller dataset, is a commonly used alternative to overcome the problem of scarcity of the data in biomedical image classification problems. Rahman And others [6], Liang and others [7], Ibrahim and others [8], and Zubair and others [9] employed solely approaches of transfer learning to classify pneumonia using different Convolutional Neural Networks models pre-trained on ImageNet [5] data.

Setiawan,and others [10] (2020) explored utilizing a CNN to detect pneumonia in chest x-ray pictures. Setiawan,and others worked on Kaggle's dataset of chest X-ray, which had a 96.30 percent accuracy. A better convolutional neural network for pneumonia identification was presented by X. Li and others [11] (2020). They achieved an accuracy of 91.41 percent when they worked on the Kaggle's dataset of chest X-ray. Raheel siddiqi[18] (2019) introduced a 18-layered novel deep sequential CNN-based model that is verified to surpass the current unconventional system in this test.

3. PROBLEM STATEMENT :

The problem statement for our project is **Predicting Pneumonia using CNN.** We will employ CNN to make the classification between a normal X-ray image and a Pneumonic X-ray image. Also we will deploy our model in an web based application so that any normal person having a lung X-ray can tell if the image is Pneumonic or not.

4. METHODOLOGY:

We have a dataset with 5,874 X-ray pictures separated into normal and pneumonic categories. Out of which 5216 are in the training dataset, 642 in the test dataset and 16 in validation datasets.

The Convolutional Neural Network (CNN), a hierarchical multi-layered neural network capable of learning visual information directly from picture pixels, is one of the most successful deep learning models. Images are fed into convolutional neural networks (CNNs), which prioritize different parts of the image. CNN does not require much pre-processing. The CNN image classifier takes an input, evaluates it, and categorizes it.

To represent and recognise the photos, we use Convolutional Neural Network architecture, which seeks to automatically create with limited domain knowledge of the problem, a high-level feature representation from low-level input is possible. Our project aims to characterize photos so that they may be identified using high-level features extracted from raw input images using convolutional and max-pooling layers, hierarchically. Each convolutional layer generates feature maps by applying sliding filters (templates) to a local receptive field in the maps of the previous layer. The map dimension decreases in layers and takes out properties that turns out to be sophisticated and general.

To recognise image classes, our proposal suggests employing a deep convolutional neural network. In general, using CNN to extract rich properties from the training dataset necessitates less domain knowledge.

Before we fit our dataset into our model we have normalized our dataset and have used data augmentation to diversify our dataset and enhance the performance of the model. The techniques used are:

- Rotating image by upto 30 degrees
- A zoom of 20%
- Horizontal and vertical shifting by 10%

Thus by doing this we can ensure randomness in the data in our dataset so that our model does not over fit and is not vulnerable to real world data.

4.1 Architecture

The neural network proposed in this project is custom and a new model was developed to compute the performance of our neural network.

Our model has four convolution layers. The first layer is the input layer consisting of 32 neurons, the activation function used is ‘relu’, stride of 1. The order of our input is 150 x 150 x 1 or we have taken a gray scale image of size 150 x 150; this was followed by “BatchNormalization” to stabilize the learning process , after that we added a max-pooling layer of 2x2 filter and a stride of 2. There are 64 neurons in our second layer, stride of 1, the activation function used is ‘relu’, then a dropout of 20% was used to approximate the training of our large dataset, this was followed “BatchNormalization” to stabilize the learning process and then a max-pooling layer of 2x2 filter and a stride of 2. The third layer is the same as of the second but in this layer we have not added dropout. The Fourth layer is similar as of the second layer but here we have 128 neurons in this layer. A flatten layer to convert our 2D array of our data to a 1D array of data. Our flatten layer is connected to a dense layer with 128 neurons with activation function of ‘relu’ and a 20% dropout was added. The output of this dense layer was the feed to another dense layer with 1 neuron. In this layer we have used sigmoid as an activation function. The output of this layer is our output of the model. Finally the model was compiled using “adam optimizer”, we have used “binary cross-entropy” as the loss function, and the metric used is “accuracy”.

“ReLU” or “Rectified Linear Unit” is a non linear activation function whose output is the input when the input given is positive and zero when the input is less than zero.

We have 1,768,833 numbers of trainable parameters to be trained. We have used 50 epochs.

```
Model: "sequential"
_________________________________________________________________
Layer (type)                 Output Shape              Param #   
=================================================================
conv2d (Conv2D)              (None, 150, 150, 32)      320       
_________________________________________________________________
batch_normalization (BatchNo (None, 150, 150, 32)      128       
_________________________________________________________________
max_pooling2d (MaxPooling2D) (None, 75, 75, 32)        0         
_________________________________________________________________
conv2d_1 (Conv2D)            (None, 75, 75, 64)        18496     
_________________________________________________________________
dropout (Dropout)            (None, 75, 75, 64)        0         
_________________________________________________________________
batch_normalization_1 (Batch (None, 75, 75, 64)        256       
_________________________________________________________________
max_pooling2d_1 (MaxPooling2 (None, 38, 38, 64)        0         
_________________________________________________________________
conv2d_2 (Conv2D)            (None, 38, 38, 64)        36928     
_________________________________________________________________
batch_normalization_2 (Batch (None, 38, 38, 64)        256       
_________________________________________________________________
max_pooling2d_2 (MaxPooling2 (None, 19, 19, 64)        0         
_________________________________________________________________
conv2d_3 (Conv2D)            (None, 19, 19, 128)       73856     
_________________________________________________________________
dropout_1 (Dropout)          (None, 19, 19, 128)       0         
_________________________________________________________________
batch_normalization_3 (Batch (None, 19, 19, 128)       512       
_________________________________________________________________
max_pooling2d_3 (MaxPooling2 (None, 10, 10, 128)       0         
_________________________________________________________________
flatten (Flatten)            (None, 12800)             0         
_________________________________________________________________
dense (Dense)                (None, 128)               1638528   
_________________________________________________________________
dropout_2 (Dropout)          (None, 128)               0         
_________________________________________________________________
dense_1 (Dense)              (None, 1)                 129       
=================================================================
Total params: 1,769,409
Trainable params: 1,768,833
Non-trainable params: 576
```

Fig. Summary of CNN Architecture used

5. RESULTS:

We had 1,768,833 parameters in our convolutional neural network to train the model. Our model got an accuracy of 91.66% with a loss of 24%. However accuracy is not the only criteria to check the validity of our model, to get more insights into our results we will be seeing the evaluation metrics.

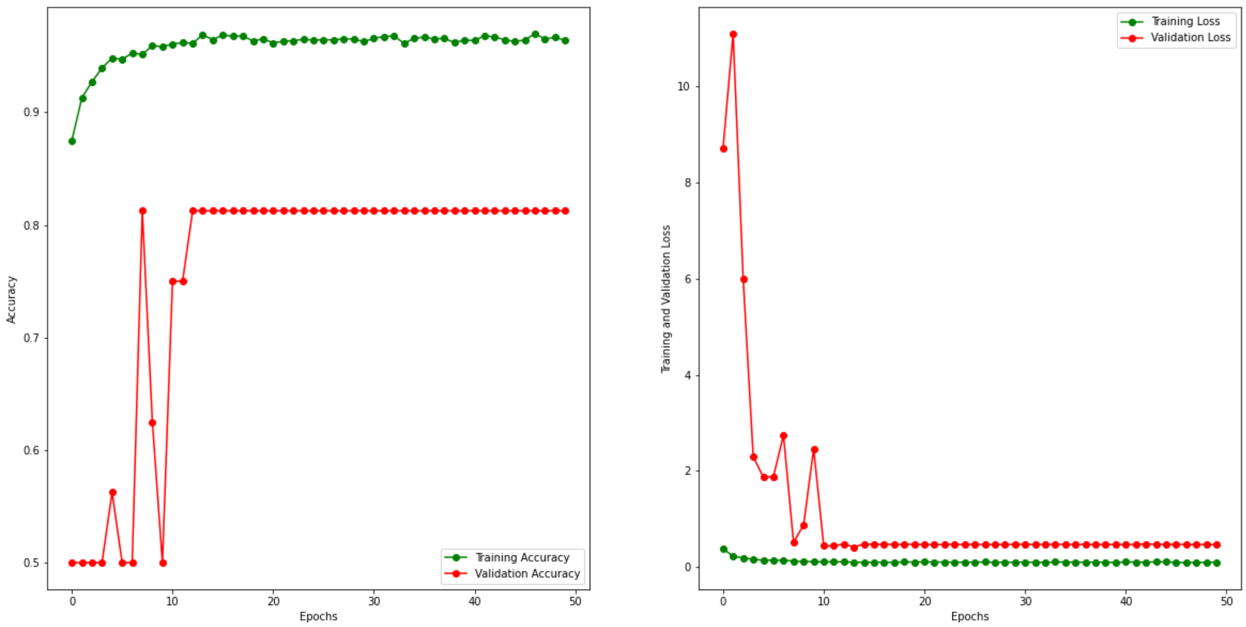


Fig. Graph of Accuracy vs Epoch and Loss vs Epoch of training data

```
20/20 [==============================] - 1s 16ms/step - loss: 0.2400 - accuracy: 0.9167
Loss of the model on test data =  0.24000400304794312
20/20 [==============================] - 0s 16ms/step - loss: 0.2400 - accuracy: 0.9167
Accuracy of the model on test data is =  91.66666865348816 %
```

Fig. Accuracy and loss results

Evaluation metrics

We employ four conventional assessment measures to assess our model on the two pneumonia datasets: accuracy, precision, recall, and F1-score. Before we establish the assessment metrics, let's define the phrases "True Positive," "False Positive," "True Negative," and "False Negative."

In our project we are basically predicting whether an X-Ray image of the lungs is Pneumonic or not , so it is a binary classification problem or the result belongs to either positive or negative class.

True Positive (TP) refers to a sample that is appropriately categorized as positive by the model and belongs to the positive class.
False Positive (FP) is a case when the model mistakenly classifies a sample from the negative class as belonging to the positive class.
True Negative (TN) is a case when the model accurately classifies a sample as belonging to the negative class.
False Negative (FN) is a case when a sample belonging to the positive class is wrongly categorized as belonging to the negative class by the model.

Formula of the four standard evaluation metrics are:

Precision $= \frac{TP}{TP + FP}$

Recall $= \frac{TP}{TP + FN}$

Accuracy $= \frac{TP + TN}{TP + TN + FP + FN}$

F1 $= \frac{2}{\frac{1}{Precision} + \frac{1}{Recall}}$

We have got the following results of Evaluation Metrics of our model:

```
Accuracy: 0.9166666666666666
Precision: 0.8823529411764706
Recall: 0.8974358974358975
F1-score: 0.8898305084745762
```

Following table is the Classification Report of our Convolutional Neural Network

	precision	recall	f1-score	support
Pneumonic	0.90	0.97	0.93	390
Normal	0.94	0.82	0.87	234

The accuracy rate is a metric that indicates the number of right predictions that a model has made. For an unbalanced dataset if the model is giving high accuracy rate it doesn’t imply that it may differentiate different distinct classes

In the medical field, for image classification, a model which can distinguish all classes is important. In such circumstances, the "precision" and "recall" numbers give us an idea about the performance of the model. The accuracy of the model's positive label prediction is indicated by "precision" defined as is the ratio of correct predictions to the total number of predictions made by the model. In contrast, "recall" refers to the true positive percentage predicted accurately by the model. These are the two metrics that are used to see if the model can reduce the amount of errors.

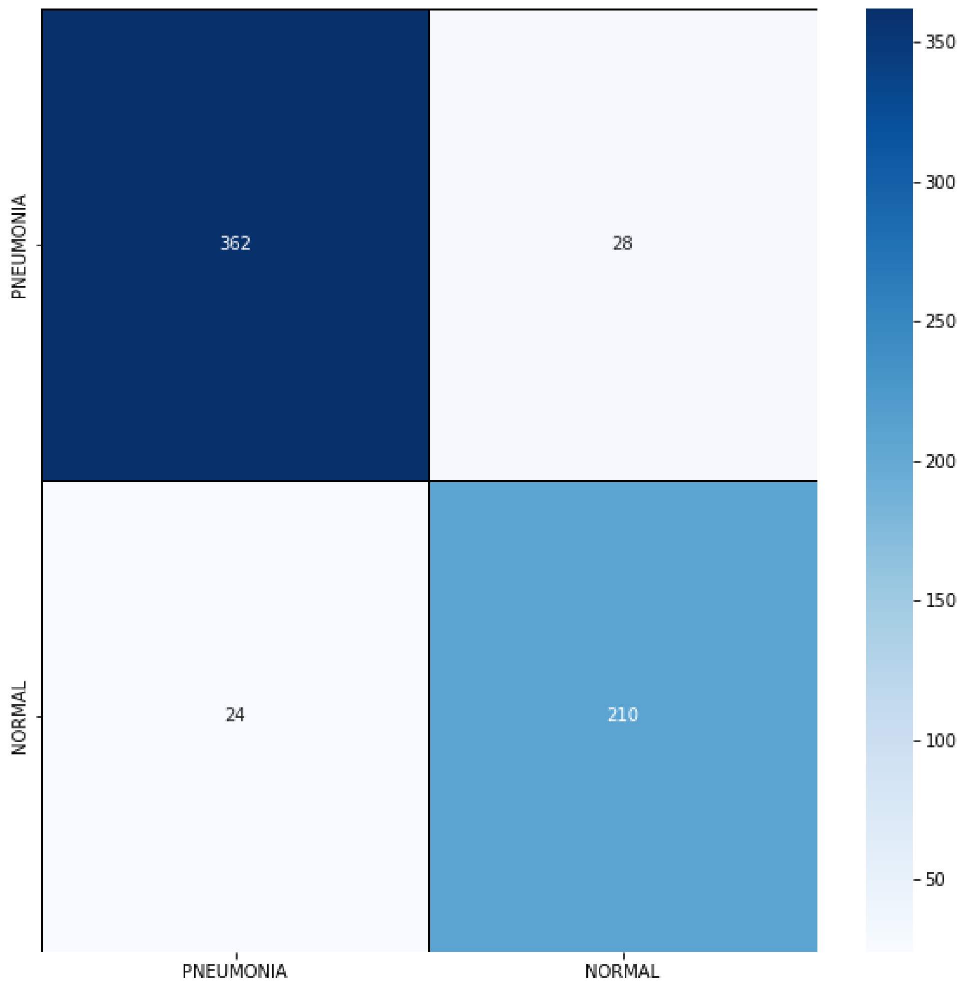
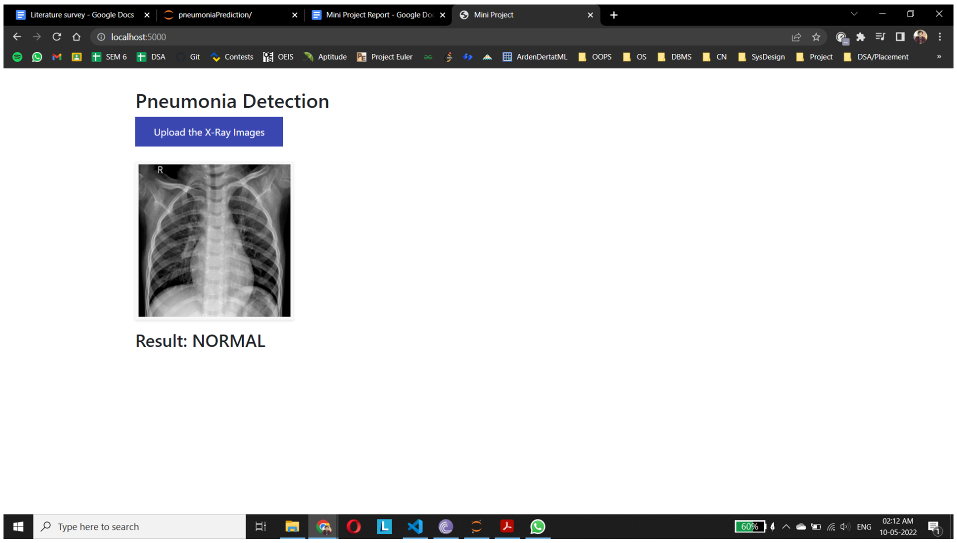


Fig. Confusion Matrix of the results

The confusion matrix was created using our training dataset. It is used to visualize the TP, TN, FP, FN cases predicted by our model.

6. CONCLUSION:

We have created a web-based application to help medical practitioners to systematize chest X-ray images into “Pneumonia” and “Normal” two different classes using categorization based on deep learning.



Screenshot of our web-based application where our project is deployed

Although we have trained our model in a large training dataset, there are chances that an image is wrongly diagnosed. To avoid this, we can use various preprocessing techniques to enhance the quality of the image. Also, explore our model with mode sample images in order to attain better results.

7. DATASET:

Training, testing, and validation folders contain subfolders for each image category (Pneumonia/Normal). There are 5,856 JPEG X-Ray images in two categories (pneumonia and normal).

URL : https://www.kaggle.com/datasets/paultimothymooney/chest-xray-pneumonia

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