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Pneumonous The Pneumonia Detector on Chest x-Ray Images using DenseNet169, Transfer Learning

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***Abstract*—In this modern world although we have advanced in every domain, still we have problems to face in the medical field, hazardous diseases are very hard to cure, pre-medication will be the biggest assert in these cases, but to do the pre-medication we need to get the diagnosis faster and accurate, it is not possible with the traditional methods. They take a lot of time for the diagnosis as after the process of biopsy and lab work, we have to take multiple opinions from the doctors. As the opinions vary from person to person based on their experience, there might be a lump of mistakes that can be done, so for diseases like pneumonia we tend to use and create new *CNN* models like VGG-16, Resnet 50, Alex-net, Densenet 121, Densenet 169 and custom models using T*ransfer learning* and building a web application for ease of use of this project to everyone, then this project will be very easy to use and the task is to simply upload the images to the website and to gain the pneumonia percentage, provided its results to the one help in need.**

Keywords—Keras, Tensorflow, Transfer learning, CNN

I. INTRODUCTION

Coming to the modern era we are overcoming multiple hurdles across various domains, we have been using the various techniques of Machine learning and deep learning in all over the fields of life, it might be in the software, business, sports, decision making, robotics, segmentation tasks etc. Also we are using the ML and DL techniques in the medical field, we are not implementing them everywhere. Like suppose we were procrastinating or feeling the symptoms of diseases like pneumonia, we will be going to the nearby medical centre, there according to the doctors opinion, the respective tests will be taken like MRI's, CT-scan etc. Then after the ordeal with the doctors conduct, we may be subjected to do the biopsy process that involves in dissection and collecting the small part of the infected area or any kind of reparative test that tells us that the patient has been affected by a specific disease and it's stage, and after the reports were out, based on the experts view(s), we will be told that, we are affected or not by the disease. This is a very long time taking process and the perspective of either doctors and experts may change based on their career experience, so one might think the patient is affected is affected to the disease and other might not, well we are humans and we make mistakes, but it is manageable even if we make some mistakes in any other field, but in the medical field, it may cost several lives. So what we do is to us the deep learning models that focuses and that are very prominent in binary image classification tasks First we need to collect the previous records of traditional methods, which are hundred percent accurate of having the disease, these records should be images, as we are doing the images classification task, so we will be giving the labels data to the model, and training the model with the existing data, and after the training, we give the unseen data to the model, and the trained model know how the images of the diseases will be, so if any similar characteristics or traits are identified in the given image, the model identifies and classifies it to the disease and non-disease category, here are some sample images from the dataset.

To have this work flow to move smoothly we need to perfectly input the data that we are using for the training to the model, that is where the preprocessing comes, making images as inputs for the model and also we need to be very cautious about the data that we are taking for the training as the that data will be the very base for the model, and the model will adjust it's learning according to the training data, this is where the collection of benchmark dataset comes into the place. Coming to the model we will be using *CNN'S***(**Convolution Neural Networks)**,** to solve the problem, in deep learning we do have models that perform well in the image class-action tasks such as VGG-16, Resnet-50, Alex-net, Densenet, first we will be using the them to get a grasp of how well the models are performing with the pre-trained weights, then we will be using the models that have only the custom layers using the *Tensorflow* and *Keras***,** these modules will be having the sub modules called layers, it is a module that contains all the layers that will be helpful to build the custom *CNN* models, then afterwards we will diving into the use of transfer learning, it is a way of using both the pre-trained weights and the custom layers which will be helping us to improve the performance and accuracy of the model for our data provided, after the models are done, we will be saving those models in the h5 format. From here we will be building the application that has a better UI, so that the ones that do not know all these ML and DL stuff can also understand the what the application is about, initially we will be building a simple application with the tkinter package that is available to use in the python, then after the initial prototype application is done wetted to deploy the application in the web, the final outcome will be a web application that will be helping a lot of people which will be having a simple UI, that takes the input as images and gives the output weather the patient is affected with the pneumonia or not along with the percentage , in this way we will be helping all those who are in need of pre-medication , even the diagnosis such as the percentage of having pneumonia is displayed in seconds, this helps way faster than any of the tradition methods.

Dataset: The data we have used is the chest x-ray images dataset, which has been used over 60 research articles and in 28 applications. It contains over 3 folders, that include test, train, val. All the folders contains the images, so this dataset is primarily used for for image classification task, at which *CNN's* perform at their prime, the model is trained over the train and test data in the dataset, and for checking over teh performance at last we have used the images from the validattion folder, which are not given to the model, hense we can see how the model is performing.

Fig: Images form the dataset

II. Literature Survey

In recent time, exploration of Machine learning (ML) algorithms in detecting thoracic diseases has gained attention in research area of medical image classification. We have taken some of the research papers for understanding more about pneumonia detection using deep learning models Maintaining the Integrity of the Specifications

1)CheXNet: Radiologist-Level Pneumonia Detection on Chest X-Rays using Deep Learning: Here they used a large database of chest X-ray images containing more than 100,000 preliminary images containing descriptions of 14 different diseases. This data is essential for training deep learning models such as CheXNet, allowing them to learn complex patterns and relationships in images to accurately identify various diseases. CheXNet, the model used in this study, is a complex 121-layer dense convolutional network (CNN) specifically designed to diagnose lung diseases from chest X-ray images.It is based on convolutional neural networks (CNNs) and was designed to assist radiologists in diagnosing pneumonia more accurately and efficiently. Using the power of deep learning, CheXNet can analyse X-ray images and provide predictions for multiple diseases simultaneously. His drawings consist of layers and layers and he tries to use and publish models to know the origin of anaesthesia pathologies. To evaluate the effectiveness of CheXNet,they have conducted a comparative analysis of radiologists' diagnoses. They evaluate the accuracy of CheXNet and evaluators by evaluating indicators such as the F1 score (which takes into account precision and recall. The results showed that CheXNet had a significant advantage, including an F1 score of 0.435 compared to the F1 score of 0.387 achieved by radiologists. This finding demonstrates the effectiveness of CheXNet in accurately diagnosing lung disease from chest X-ray images, even outperforming experienced human operators on some diagnostic tasks. Overall, this study demonstrates the great potential of deep learning models such as CheXNet to improve clinical diagnosis. Through the use of digital technology, these models can support doctors to make more efficient and effective diagnoses and ultimately improve patient outcomes.

2)Pneumonia Detection Using an Improved Algorithm Based on Faster R-CNN In this paper, They proposed a DeepConv-DilatedNet-based method to identify and localise pneumonia in chest X-ray (CXR) images.The DeepConv-DilatedNet-based method represents a cutting-edge approach in the domain of deep learning for image analysis and understanding. This method leverages the power of dilated convolutions, a key architectural component that enables the network to capture both local and global contextual information effectively. By employing dilated convolutions, the receptive field of each neuron's can be expanded without significantly increasing the computational cost, allowing the network to capture spatial dependencies across a wider range of inputs. Two-stage detector Faster R-CNN was used as the network model. Insert the Feature Pyramid Network (FPN) into the remaining neural network that exposes the bottleneck, thus expanding the deep features to preserve the deep features and location information in the products. In the case of DeepConv-DilatedNet, a deconvolution network is used to restore the high-order feature map to its original size and further store the target information. DeepConv-DilatedNet, on the other hand, uses the most popular convolutional architecture in which calculations are shared across the entire image. Then use Soft-NMS to check the box and make sure the sample is good. Additionally they used K-Means++ is used to create junction boxes to improve location accuracy. This algorithm achieved a mean accuracy (mAP) of 39.23% on the Radiological Society of North America (RSNA) X-ray image dataset and a mean accuracy (mAP) of 38.02% on the ChestX-ray14 dataset, compared to other findings.

3)Pneumonia detection in chest X-ray images using an ensemble of deep learning model This study, they created a network consisting of three networks: GoogleNet, ResNet-18 and DenseNet-121. The GoogleNet architecture represents an advance in deep neural networks, especially for computing tasks. Unlike older models that follow the process, GoogLeNet introduces the concept of "initialisation module" to achieve better results and provide learning representation.The ResNet-18 model represents a significant advance in deep neural network architecture, particularly in image recognition. The essence of ResNet-18 is a new concept of residual learning that revolutionises deep learning techniques. Residual learning solves the challenge of training deep neural networks by teaching residuals. These blocks optimise the entire network architecture by determining the rest of the process model. Unlike traditional methods that rely on layers to learn complex representations, ResNet uses residual connections (also known as “skip connections”) to facilitate the learning process. DenseNet represents a significant advance in deep neural network design, providing better representation and computational performance. At the heart of Dense net is a network architecture that creates a seamless network that allows data to flow across the web. Result A joint model was developed that considers the weighted average of the joint results obtained from three CNN models (GoogLeNet, ResNet-18 and DenseNet-121). The weights assigned to the classifiers are calculated from the new input by doubling the curve tangent function fuses. four evaluation parameters: precision, recall, f1 score and AUC. The framework was evaluated on two chest x-ray datasets and achieved 98.81% accuracy, 98.80% sensitivity, 98.82% 8.79% and 9% f1 score on the Kerman dataset. Accuracy rate RSNA matching using five-fold cross-validation scheme In the data, the sensitivity rate is 86.86%, the precision rate is 87.02%, and the precision rate is 86.89%. F1 score is 86.95%. best approximation on both datasets.

4)Pneumonia Detection from Chest X-ray Images Based on Convolutional Neural Network:In this paper, they obtained data from the Kaggle competition, which contains a total of 5786 X-ray images. Additionally the file is divided into three folders (train, test, val) and there are subfolders for each image group (lungs / valves). All chest x-rays (front and back views) are from patients ages 1 to 5 years. To show the wide range of different models, the main files are divided into three folders to provide a 70%, 10% and 20% test. They previously use Resize, normalise, Rotation_Range, Zoom_Range, Weight_shift_Range, Height_shift_range, Horizontal_flip, Vertical_flip. According to the performance summary of different models, including three models with and without residue, VGGMobile, ResNet50, Net, Inception and DenceNet121 (DenceNet50, DenceNet50, Dense input form is 224 and loss) BC function. It is seen that the performance of the first model created with the differentiation process is higher than the original model that was not developed. Moreover, the table shows that our proposed model achieves the best results with an accuracy of 0.9607 and precision of 0.9441. It can also be seen that DenceNet121, which is only 0.9342, the performance of the model before using different technology achieved more than 0.94 accuracy, and our design is acceptable when compared with the model performance of the old model without improvement. 0.953 accuracy Most accurate. Effect of augmentation method on CNN model.

5)Pneumonia Detection using CNN based Feature Extraction:The data used in this paper is publicly available on the Kaggle platform and includes 112,120 frontal chest X-ray images from 30,085 patients. Each radiograph in the database was tagged with one or more of 14 different breast lesions. The text is derived from classifying mining errors in electronic information related to natural language processing (NLP), with an accuracy estimate of over 90%. For the purpose of this study, we think that the text is accurate for the diagnosis of lung disease by following the previous process. Before the publication of these data, the largest X-ray database was Openi, which contained approximately 4,143 X-ray images. However, the results obtained using features extracted from many different models before CNN suggested DenseNet-169 as the best model for scene feature removal. Therefore, at this stage, the DenseNet-169 model architecture and its contribution to feature extraction are mainly explained. We can conclude that the combination of formal models, CNN-based feature extraction, and supervised classifier algorithm constitutes the best solution for classification of abnormal (pneumonia markers) and images. Chest x-ray is always due to the important features of DenseNets and Optimal hyperparameter;

6)Review on Pneumonia Image Detection: A Machine Learning Approach This article explores and evaluates whether computer-aided diagnosis can be used to diagnose lung disease. It also offers a hybrid model that can effectively detect lung disease while using real-time medical data confidentially. This article explores various imaging techniques, such as X-rays, that can identify and diagnose a variety of diseases. The research also examines how different learning techniques such as convolutional neural network (CNN), k-nearest neighbour (KNN), RESNET, CheXNet, DECNET, and firefighter neural network (ANN) can be used to diagnose lung diseases. In this article, they conduct a qualitative analysis of data to learn how hospitals and clinics can combine to train learning models from their own data so that machine learning algorithms can detect viruses better and more accurately. This paper uses the deep learning models of RestNet-101 and RestNet50 for lung disease diagnosis. When thinking about these ideas, different results are created depending on individual characteristics. Therefore, an in-depth study involving the integration of these methods has been introduced to bridge this gap. In this study, data from 14,863 X-ray images were used and an accuracy of 96% was achieved. Although the model shows good accuracy, the hybrid model has limitations due to the complexity of RestNet, which may affect the accuracy when determining larger data in emergencies.

7)Pneumonia Detection using Convolutional Neural Networks This paper presents a neural network model that can detect pneumonia from a chest X-ray, which doctors can use to treat pneumonia in the real world. Experiments were performed on the chest x-ray image (pneumonia) dataset available on Kaggle. The first, second, third, and four models include one, two, three, and four convolution layers.The accuracy of the first model reached 89.74%, the accuracy of the second model reached 85.26%, the accuracy of the third model reached 92.31% and finally the accuracy of the fourth model reached 91.67%.The second, third and fourth models consistently use Dropout to reduce overfitting across all layers.

III. METHODOLOGY

Alex-net: It is a convolutional neural network(CNN) used mainly to determine the image classification.It provides the higher accuracy when compared to the other methods which are used in image classification domain.It uses multiple convolutional layers to achieve the higher accuracy results.Chest x-ray images were obtained from the kaggle, the dataset consists of two classes one is normal or the chest x-ray of the normal person and the other one is abnormal.

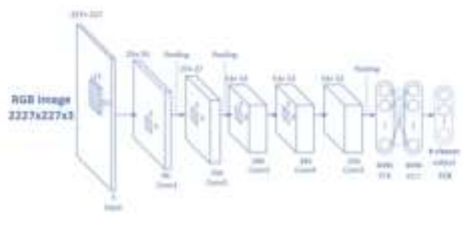

Fig: Architecture of Alex-net model

The alexnet Architecture is used as the convolutional neural network i.e is CNN.This Architecture consists of the five convolutional layers combined with the max-pooling layers.It uses the following architecture: The first convolutional layer consists of 96 filters and the kernel size is 11x11 with the stride value as 4x4. The next or the following convolutional layers with filter size of 256,384 and 256 with different kernel sizes and activation functions. The feature maps were passed through three fully connected layers with 4096 neurone each, activated by ReLU functions, and the final layer with two units for binary classification was activated using softmax activation. The alexnet is fitted with the Adam optimizer with a learning rate of 0.0001.The alexnet model is fitted with the 5 epochs on the training data and the batch size is also constant 32 for this architecture so that we can achieve higher accuracy results on the training data.To achieve the generalisation ability of the architecture we even evaluated the independent test sets. and at last we even recorded the model accuracy and loss for each epoch to analyse the training on the model and also to observe the overfitting of the alexnet. The alexnet architecture was checked or evaluated to classify chest x-ray images as normal or abnormal.After getting the higher accuracy by changing the number of epochs the trained model was saved for the usage of model in the upcoming ,predictions.The saved model file,model_transfer_learning.h5,contains the trained model.

Resnet50: It is a convolutional neural network(CNN) architecture which is also used in image classification domain.It contains 50 convolutional layers which is developed by the Microsoft research for the image classification.Chest x-ray images were obtained from the kaggle, the dataset consists of two classes one is normal or the chest x-ray of the normal person and the other one is abnormal i.e the chest x-ray of the person who has pneumonia.The Resnet50 architecture is also used for thr prediction of the chest-ray images which has pneumonia or normal.

The Resnet50 is pre-trained on the ImageNet dataset.We have added the extra convolutional layers for the Resnet50 Architecture so that we can perform the prediction on the chest x-ray images which is normal and which is abnormal. A flatten layer was added to get the output as required by us. It also contains a dense layer with 512 neutrons and also we have added the ReLU activation for the capturing of high-level features in the chest x-ray images so that we get the higher accuracy results.we also kept an eye on the model so that it would not be overfitted model with the dropout regularisation with the rate of 0.5.we have also added the Adam optimizer for the model, which had helped us to achieve or to minimise the loss function.

VGG16: The VGG16 is a convolutional neural network (CNN) which was created by the Visual Geometry Group. The 16 in VGG16 refers to the total number of layers in the model consisting of 13 convolutional layers and 3 fully connected layers.The images were preprocessed by redefining them to a standard size of 224x224 pixels and rescaled to values in the range [0, 1]. It contains 13 convolutional layers and it consists of max-pooling layers.

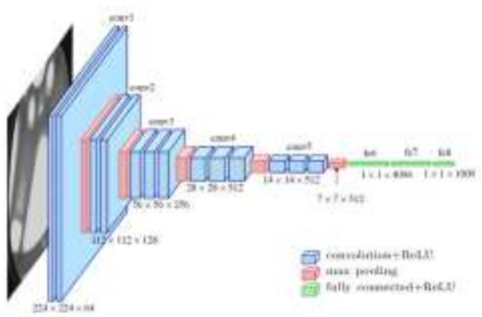

Fig: Architecture of VGG16 model

It uses 3x3 filters with a stride of 1 and also the padding value is 1, while the max-pooling layers use 2x2 filters with a stride of 2.Custom dense layers were added to the VGG16 base model to change it for the binary classification task. The added layers included two dense layers with 4096 neurons each, followed by dropout layers with a dropout rate of 0.5 to check for overfitting in the architecture.The VGG16 even captures the more complex images from the input images.The main reason for using the VGG16 architecture is that it uses the uniform architecture though out the process i.e it has the same filter size and stride and even the max-pooling layers have the same filter size and stride value same as the main architecture in the VGG16.The model was trained with 5 epochs with a batch size of 32. During training, the model's performance was evaluated on the validation set to monitor for overfitting and also for the generalisation ability.This architecture mainly uses transfer learning as a feature extractor. It also uses pre trained weights on image datasets such as the ImageNet.The loss and validation loss metrics were plotted using matplotlib to visualise the training process.Upon completion of training, the trained model weights were saved for future use and deployment.

DenseNet121: It is a deep convolutional neural network(CNN) which is known for its dense connection pattern where each layer input is received from all the preceding layers.Due to these factors the DenseNet121 is the best choice in the image classification domain.Chest x-ray images were obtained from the kaggle, the dataset consists of two classes one is normal or the chest x-ray of the normal person and the other one is abnormal i.e the chest x-ray of the person who has pneumonia.The images were preprocessed by resizing them to a constant size of 224x224 pixels. In this DenseNet 121 the pre-trained ImageNet is chosen as the base model for transfer learning.

The highest classification layers of DenseNet121 were removed and the dense layers were added to adapt the model for the binary classification or in simple words we can tell like for prediction of the chestX-ray images.The DenseNet121 contains two dense layers with 512 and 256 neurons.We have also added the activation functions like ReLU.We have added the dropout layers with the dropout of 0.5 to check for overfitting of the model.In this DenseNet121 we have used the Adam optimizer with a learning rate of 0.0001 during the training of the DenseNet121 architecture.

The DenseNet121 model is fitted with the 5 epochs on the training data and the batch size is also constant 32 for this architecture so that we can achieve higher accuracy results on the training data.To achieve the generalisation ability of the architecture we even evaluated the independent test sets. and at last we even recorded the model accuracy and loss for each epoch to analyse the training on the model and also to observe the overfitting of the DenseNet121.The DenseNet121 architecture was checked or evaluated to classify chest x-ray images as normal or abnormal.Upon completion of training, the trained model weights were saved for future use and deployment.

DenseNet169: The DenseNet169 represents a formidable advancement in convolutional neural network (CNN) architectures, distinguished by its innovative dense connectivity pattern. Unlike traditional CNNs, DenseNet fosters intricate connections between layers, where each layer receives input not only from its immediate predecessor but also aggregates feature maps from all preceding layers. This dense connectivity facilitates the seamless propagation of features throughout the network, promoting feature reuse and addressing the challenge of vanishing gradients. DenseNet169 specifically comprises 169 layers organized into densely connected dense blocks. These blocks consist of multiple convolutional layers, and their interconnection forms a network that excels in feature extraction. Beyond its connectivity, DenseNet169 incorporates growth rates, which determine the number of feature maps added to the network at each layer, and bottleneck layers for computational efficiency. This architectural innovation enhances the model's ability to learn intricate hierarchical representations, making DenseNet169 particularly effective for tasks like image classification.

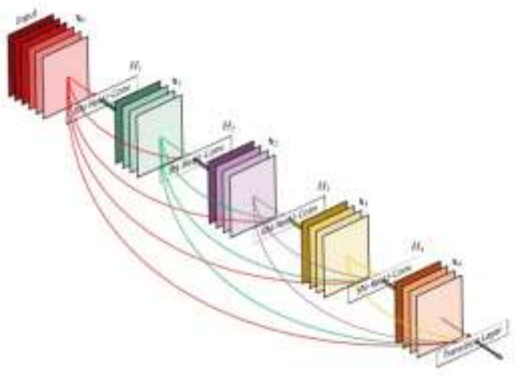

Fig: Architecture of Densenet

In the Implementation part the model meticulously translates the DenseNet169 architecture into a practical solution for binary classification of chest X-ray images into normal and abnormal categories. Leveraging a pre-trained DenseNet169 base model, excluding the final classification layers, the script augments the architecture with additional dense layers. Specifically, two dense layers with 1024 and 512 neurons, complemented by Rectified Linear Unit (ReLU) activation functions, contribute to robust feature extraction. To mitigate overfitting, dropout layers with a dropout rate of 0.5 are strategically inserted. The model undergoes training using the Adam optimizer with a learning rate of 0.0001, spanning five epochs and employing a constant batch size of 32 for stability. Introducing data augmentation techniques, including rescaling, shearing, zooming, and horizontal flipping during training, enriches the dataset and enhances the model's generalization capabilities. Throughout the training process, the script records accuracy and loss metrics for each epoch, ensuring a comprehensive analysis of model performance. Subsequently, the model is rigorously evaluated on an independent test set to assess its generalization ability. The code goes further to generate informative loss and accuracy plots, which are not only instrumental for visualizing training dynamics but also insightful for identifying potential overfitting. The culmination of this implementation involves the prudent saving of trained model weights, laying the groundwork for future deployment and application in real-world scenarios. Abbreviations and Acronyms.

The implementation of DenseNet169 in the provided code strategically incorporates transfer learning, a pivotal technique that significantly enhances the model's effectiveness. Transfer learning leverages the knowledge gained by a pre-trained model on a large dataset and applies it to a new, related task. In this context, the script utilizes a pre-trained DenseNet169 base model, which has learned rich hierarchical features from a diverse dataset. By excluding the final classification layers and adapting the model for binary classification of chest X-ray images, the architecture becomes proficient at extracting relevant features specific to the medical imaging domain. This approach not only accelerates convergence during training but also allows the model to capitalize on the learned representations from the broader dataset, leading to a more robust and finely tuned model for the task at hand.

The introduction of transfer learning has a pronounced positive impact on the performance of DenseNet169 for chest X-ray classification. By initializing the model with weights learned from a broader dataset, the network starts with a strong foundation, capturing generalizable features that transcend specific domains. As a result, the model exhibits improved convergence during training, showcasing a faster and more efficient learning process. Furthermore, transfer learning mitigates the risk of overfitting, especially when working with a limited dataset, as the model has already learned relevant hierarchical representations from diverse examples. This approach enhances the model's ability to generalize to new, unseen chest X-ray images, ultimately contributing to elevated accuracy and robustness in the classification task. The combination of DenseNet169's architecture and the strategic utilization of transfer learning establishes a potent framework for accurate and reliable chest X-ray image classification.

IV. WORKFLOW

A. First phase

Initially we have we have worked on three models which are vgg-16, Resnet-50, Alex-net, then we have claculated the accuracies of the models whcih are as the table mentioned in below, these are the first phase results.

ALGORIMHS USED	*ACCURACY*
VGG-16	88.94
Resnet- 50	62.50
Alexnet	86.86

Table: Accuracies of first phase

B. Second phase

In the second phase we have learned about the transfer learning, and implementer the transfer learning, to the best performed model which is VGG-16, so after implementing transfer leaning, the model has shown an improvement of accuracy and we have used the tkinter module in python to have a simple user interface that takes the input as images fron the local system and predicts the Pneumonia percentage.

ALGORIMHS	*ACCURACY*
VGG -16	88.94
VGG-16 With Transfer Learning	90.87

Table: Accuracies of second phase

Then we have saved this model as .h5 file and built a sample graphical user interface application that interact with us, there will be button in the application, which allows the users to give the image input to the model, so by clicking on the images that we desire to get the pnueminia percentage, the application displays the percentage.

Fig: The tkinter application of the second phase

C. Third Phase

Here in the third phase we have thought that, we should go for a complex model, and we need to make a web application, so we have choosed to know more about densenet, so we have implemented both the models densenet 121 and densenet 169, along with transfer learning, the accuracies were mentioned in the table below.

ALGORIMHS	*ACCURACY*
Dens enet 121	91.35
Densenet 169	91.99

Table: Accuracies of third phase

D. Final Phase

Now we have completed all the models that we have to implemente we have started to build a website with the technologies HTML, CSS, Java Script, Flask, at first we have built a basic website that uses html and css, the below image represents the first prototype of the website.

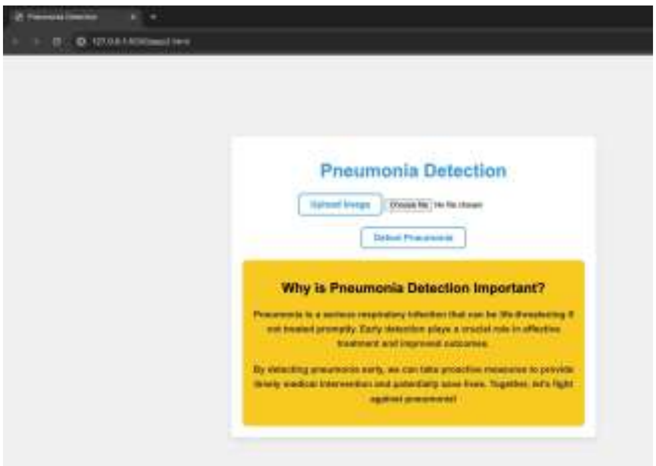

Fig: Initial prototype of the website

After that we have also included the backend which runs on python, and then we have connected to the model, that is Densenet 169 with transfer learning. Also we have added some more styling than to the prototype website, we have name this website as Pnuemonous - the Pnuemonia detector, which has a beautiful interface and css hovering effects, this website also provides the info and history about pnuemonia and how it is started, and similarly it also contains an upload button, which will ask for the image throgh the system path, and the percentage of pnuemonia is bing displayed in the article element which is right aligned to the webpage.

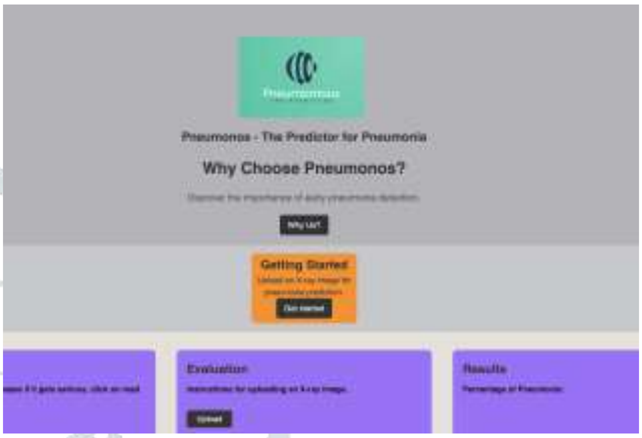

Fig: Overview of Pnuemonous

V. RESULTS

We have devloped an interactive website that takes the images from the user and provides the Pnuemonia percenatge, the algorithm that has been finally used is Densnet 169 with Transfer Learning, which performed better than the other algorithms that we have implemented, with the accuracy of 91.91 percentage. The final accuracy table was given below, that contains all the models that we implemented from the first phase.

ALGORIMHS USED	*ACCURACY*
VGG -16	88.94
Resnet- 50	62.50
Alexnet	86.86
VGG-16 With Transfer Learning	90.87
Dens enet 121	91.35
Densenet 169	91.99

Table: Accuracies of all models used

VI. CONCLUSION

We have succesfully implemented multiple deep learning models fotr the Pnuemonia image classification task, and selected the best model for evaluating the images that are provided to teh model. Also we have succesfully created a website called as Pnuemonous with beautiful user interface, which will be benificial for many users in the medical field, so it will be a kind of pre-medical application.

VII. FUTURE WORKS

The future work of this project is to host this website and the devloped model to the cloud, we were looking for the website which provides a resonable price for cloud hosting, and we have to integrate a html page at the results article in teh website, so that based on the percentage, the precautiuons and remidies to be recommend, which makes this website more reliable.

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