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CNN BASED CHEST X-RAY CLASSIFICATION

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ABSTRACT

India faces acute shortage of radiologists. As per NCBI, USA India has one radiologist per 1,00,000 people. In past two years we have seen unprecedented COVID-19 pandemic which has posed a huge burden on our health care infrastructure and health care professionals. The rural parts are hit worst struggling to provide lifesaving health care access causing millions of Indians to lose their lives. In this regard our project focuses on developing a web based application which may reduce the burden on health care professionals and help in timely diagnosis of chest x-ray findings without delays and withprecision. This will help to treat patients with utmost care, can avoid unnecessary surgeriesand save lives.
In the recent years Artificial Intelligence(AI) empowered systems have proven to be dominant in all domains. Artificial Intelligence has attracted most of the researchers of therecent past. Artificial Intelligence which encompasses all the industries has been proven tobe vital in Health care by helping healthcare professionals in taking decisions and also in diagnosis and detection of several critical ailments like cancers and others.
In this project we have leveraged the transfer learning as benchmark to obtain the models for our task of classification. We have executed the experiment through the various standard models available retaining the similar experimental conditions and did the comparative analysis to evaluate them and to pick the best one among them. The results achieved show that Densenet-169 provided the best results with 95.56 percentage validation accuracy which has been used for making predictions in the web application.

INTRODUCTION

Access to healthcare is one of the basic and most important necessity for the human life when compared other necessities of life. India is a country of villages which directly takes us to conditions where we are striving to provide with basic amenities. During last two years the healthcare and the healthcare professionals are over burdened with the pandemic since our population and the health care facilities are still not matching the expected thresholds especially in the rural regions of the nation. The pandemic has made us understand that the healthcare needs to upgraded drastically and it needs scaled up as per the need of the hour. The reality is that we cannot overcome the acute shortage of doctors and other support staff and we cannot scale up the human resources overnight to match the needs instead we can assist the working professionals with technology to speed up the diagnosis by automating the processing of the different medical tests conducted during the process of treatment and we can draw inferences from the tests through artificial intelligence powered systems without waiting for the human to interfere and extract the results from the tests.
Chest X-ray is one of the predominant test carried out to diagnose the ailments in the chestregion and can study the abnormalities if any in the internal organs like heart and lungs. The procedure is not invasive in nature and we can derive the results swiftly. The bottleneck in this case is the availability of the radiologists who will examine the chest x-ray and reportthe findings to further treatment. As specified earlier we face shortage of radiologists which will delay theprocess of treatment.
Deep Learning inset of Machine Learning(ML) which deals with Artificial neural networks is performing exceptionallywell in the areas of Computer vision (consisting of Imagerecognition and object detection) and speech recognition.
Deep Learning (DL) especially Convolutional Neural Networks (CNNs) have given extremely good outcomes in the image classification by doing exceptionally well in featureextraction tasks.
In this project we are leveraging the most important potential of CNNs through transfer learning where we use the previously trained CNN models to classify the images of chest X-ray. Convolutional neural networks are trained with Chest x-ray images to extract the
features in them and later classify them whether there are any findings in them or they areNormal.
The pre trained models like VGGNet, Xception, Inception, ResNet, DenseNet and NASNet which are trained on largescale dataset like ImageNet are employed to our required task of feature extraction and image classification task at hand.
We do a comparative analysis of the results based on the metrics for which the model has been evaluated. We find a best model to use it in the web based application for making predictions.
There are different services offered to combat the shortage of the radiologists like Teleradiology where the radiologists located far away from the patients receive the transmitted digital radiographs and examine them and provide the diagnosis. But yet there is a human radiologist sitting at the other end and doing the duty. Again since the radiologists are getting overloaded from the demand from every geographical area we mayface lag in obtaining results. Our work goes further to remove this bottleneck of having radiologists to infer the chest x-ray by delegating the task to the artificial intelligence enabled machines which can work round the clock without fatigue and with same precision on each case it handles.

PROBLEM STATEMENT

Diagnosis of the chest x-ray to pick up the inferences is a skillful task and requires expertisein the job. Several images may get misinterpreted as different diseases since the images will be unclear and ambiguous. India faces shortage of these skilled radiologists to meet the growing demand due to increase in population and hence leading to poor access to health care especially in remote areas and over burden on the currently serving professionals. Developing an artificial intelligence powered system to diagnose and report the results will help us to extend the access to healthcare to the remotest part of the countryand help us in saving lives.

EXISTING SYSTEM

The images of chest x-ray are examined by a radiologist who is trained and possessing expertise will study the image and report the findings so that doctors will decide and plan the treatment of the patient accordingly. The speed with which the treatment is given to the patient relies on how fast we diagnose the chest x-ray and get the result report. This phaseis very crucial to patients since delay in the diagnosis and starting the treatment will lead to increase in the severity in the disease. In several cases timely diagnosis can avoid unwanted surgeries also. Due to less number of available radiologists they are overloaded and hence we suffer delays in getting results.

DEMERITS OF THE EXISTING SYSTEM

The existing procedure requires an expert radiologist to examine the chest x-ray andreport the findings.
Expert radiologists are very less in number and are overburdened.
The turn around time to get the results increase with increasein number of patients.

Every radiologist needs the same level of expertise and should work without fatigue.

PROPOSED SYSTEM

The proposed system is an artificial intelligence empowered web application hosted in a typical web server which will receive the image of chest x-ray from the user and uses the deep learning model which will diagnose the image and report us the findings.

MERITS OF THE PROPOSED SYSTEM

The proposed system will help us provide access to healthcare to the rural areas as well.
The system will scale up and handle the demand in case of pandemic and will reduce the burden on the healthcare professionals.
The system will reduce the dependency on the radiologists and help us diagnose faster.
The system has consistent accuracy and precision dealing with all the cases and it does notsuffer fatigue.

LITERATURE SURVEY

Dimpy Varshni et al. [1], worked on the chest x-ray classification using CNNs for feature extraction in which they have worked on ChestX-ray14 dataset which was released by Wang et al. In their work they used various CNNs for feature extraction and presented them to the various classifiers and did an analysis to find the best CNN and the classifier. Their work focussed on the binary classification of the images whether the images have pneumonia or normal They have reported the best accuracy of 80.02 % with DenseNet-169 for feature extraction and SVM as the classifier.
Hongyu Wang et al. [2], have proposed a deep CNN named ChestNet for the identificationand classification of thoracic ailments through the chest radiographs. Their work put forth a model which was divided into 2 sub sections one was a classification and another one was called attention section which dealt with leveraging the interdependence between the target class labels and the areas of the abnormalities found in the pathology and adapts themodel to focus on only the areas with abnormalities.
Rahib H. Abiyev et al. [3] in their work studied the different models built which are based on deep CNNs, Back propagation neural networks which is supervised learning and competitive NNs which are based on unsupervised learning. The results shown that when recognition rate was used as comparison factor the back propagation neural networks outperformed the competitive NNs.
Pranav Rajpurkar et al. [4] have developed a model CheXNet based on Dense CNN which possess 121 layers. These networks are better at flow of gradients and details through the network. Their work shown that the ChexNet was superior in performance when compared to radiologists in the F1 score metric.
T. Rahman et al. [5] have worked on publicly available dataset through kaggle to classify the images as pneumonia and normal and further they have worked to classify them as viraland bacterial pneumonia. They have employed different previously trained models like ResNet, AlexNet, DenseNet and SqueezeNet. They have worked with 5247 images. Their work has demonstrated that DenseNet201 has outperformed other models and achieved accuracy of 98% during classification of images into normal and pneumonia, accuracy of 95% during classification of images into viral pneumonia and bacterial pneumonia and accuracy of 93.3% during classification of images into all the three categories.
Their work
states that transfer learning can be leveraged to classify chest radiograph images quiteeffectively.

SYSTEM REQUIREMENT SPECIFICATIONS

A good quality SRS is highly recommended in order to achieve good quality software. The requirements elucidated should be aligned with all the stakeholders of the project. The requirements should obey all the characteristics suggested for a good SRS. In this chapter we define the requirements of the system at a high level.
DESCRIPTION OF FUNCTIONALITY IN TERMS OF USE CASES
In this section we specify the necessary functions of the system through use cases which describe functionality by extracting the interactions conducted by the user with the system.It also encompasses the behavior of the system.
UC1: Disease Prediction of an image

Primary actor: User

Precondition: The user has navigated to the Home page of the web application.
Main expected Scenario:

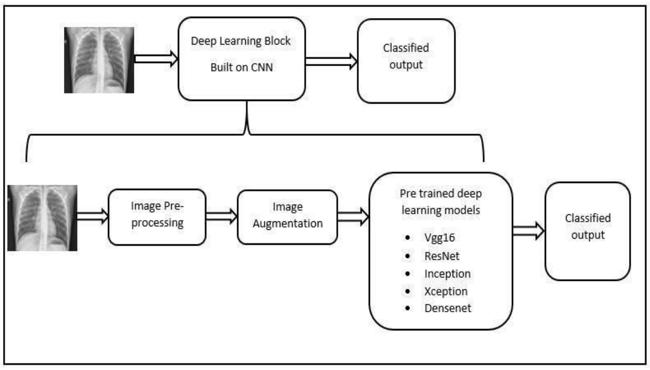
User selects the image through the browse option by Choose

file button in the web page User posts the selected image to the web server
User clicks on the predict button to know the displayed results of the prediction.
Exception Scenario:
The user tries to upload a file which is not supported. The only supported files are images of jpg, jpeg, png and gif formats. System alerts the user by displaying proper image.

SYSTEM DESIGN

SYSTEM ARCHITECTURE

The proposed system has an architecture as shown in the figure



4.1 below.

Figure 4.1 Showing the architecture of the system.

The block diagram depicts the overall architecture of the system where it illustrates the important components which are explained in this chapter. The system takes input in the form of chest x-ray image which is fed in to deep learning block for the classification. Theclassified output is rendered to the user through the web page.

TRANSFER LEARNING:

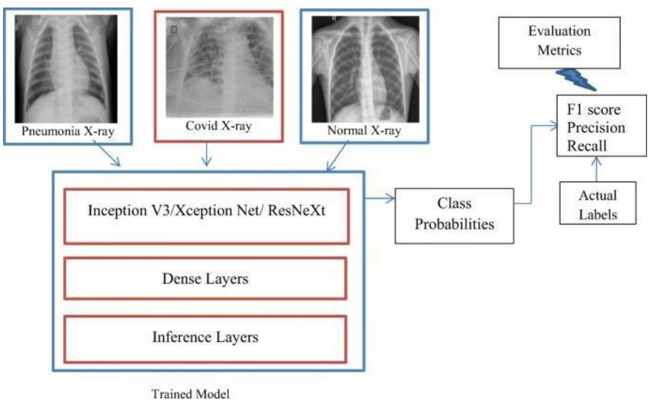


Figure 4.2 Showing the architecture of transfer learning.

The project leverages technique known as transfer learning where in the models which are trained over a large dataset like ImageNet [6] can be adapted to similar classification taskswith respect to smaller datasets. This technique may be used in different scenarios.
We can use different models with the already learnedweights straight away in similar image classification tasks. We can leverage the previously trained models with learnedweights and these weights can be used as initial weights instead of random weights in training the models with new datasets which will help the models to converge faster.
We can use the pre trained models and train only the last few layers of the neural network by freezing the initial layers which can prove effective in fine tuning the model to the task in hand.
Figure 4.2 depicting the transfer learning process

The transfer learning involves adapting the previously trained model to suit the needs of the task in hand since models trained on ImageNet dataset are trained for object detection of 1000 classes. The process of adapting is shown in the figure 4.3 below.

IMPLEMENTATION

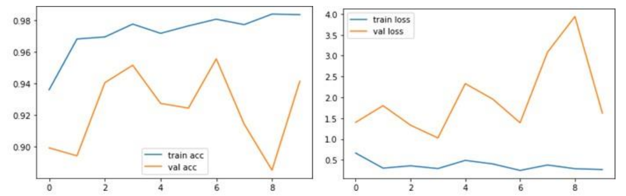
The initiative is put into action in two parts.
1. Creating and training various application models to find the optimal model through comparison.
2. Creation of a web application for loading the best model and making predictions using the Flask web framework.
The computer language Python was used to create the project. For the development, training, and testing of the models, Jupyter Notebook is the IDE utilized. The web application is developed using Spyder IDE.

DATASET

The dataset used in this investigation was chest x-ray, which is downloadable online. The collection contains 112120 frontal images of chest x-rays at a resolution of 1024 × 1024. The 30805 patients represented by these images are. The pictures include labels and represent 14 different thoracic illnesses. The labeling was done using Natural Language Processing (NLP), a text mining technique. There are numerous disorders, including effusion, pneumonia, atelectasis, cardiomegaly, consolidation, pleural thickening, infiltration, nodule, pneumothorax, hernia, emphysema, edema, mass, and fibrosis. In my project, I used images from the normal, effusion, and pneumonia categories. Since I only had a small number of images of pneumonia, I submitted pictures from another Kaggle dataset. I used 87 photos for testing, 1014 for validation, and 8726 from three courses for training.
IMAGE PRE PROCESSING AND AUGMENTATION:
Before training, pre-processing and photo augmentation are essential steps in customizing the visuals to the model's requirements. The Keras library provides the ImageDataGenerator class. This class can be instantiated to produce an object, which is particularly useful for image pre-processing. I can perform image pre-processing by passing inputs to the object constructor.
I can improve photographs using the parameters shown below:
• Increasing the image's zoom by entering zoomrange=0.2.
• Rotating the image by turning on the True value for the horizontal flip attribute.

• Setting rescale=1/255.0 to rescale the image so that all pixel values fall between 0 and 1.
(datagenerator obj = ImageDataGenerator, zoom range =0.2) shear range = 0.2, rescale = 1 /255, and horizontal flip = True.
The flow from directory method of the ImageDataGenerator will help us with
• Load the dataset in batches. I can pass a parameter to the function that specifies the batch size.
• By including a parameter to the that specifies the input size that the models require, I can additionally resize the image to 224 224.
CREATING AND ADAPTING THE PRE TRAINED MODEL:
The deep learning model that needs to be trained should first be built and modified as necessary to meet the needs of the project. The model is often built as an object of a certain model class. • I may delete the top layer, which is the output layer, by providing include top = false. I can supply other parameters to the constructor to make appropriate modifications in the model as needed.
• The parameter input shape=224 x 224 x 3 allows to choose the input shape of the model.
• we can use the pre-trained weights by using the weights = iamgenet parameter.
we can modify the model by adding our dense layers, such as a classification layer with n neurons in the output layer.
COMPILING THE MODEL:
The model can be generated and changed, then compiled using a function named compile. The compile function call's target should be the model object. The compile function options allow for specifying a variety of instructions for the model that should be followed during training.
• I can tell the model to utilize a certain loss function during training by using the parameter labelled loss. For example, loss equals categorical crossentropy.
• I can choose the optimizer that needs to be used by using the argument named optimizer. For instance, optimizer = Adam
• I may offer the metrics to monitor during training using the "metrics" option. It's true that I can define a set of measurements. As an example, metrics equal ["accuracy"].
TRAINING THE MODEL:
In order for the model to learn the characteristics from the data, it needs be trained using the dataset. Learning occurs during both the feed-forward phase and the back propagation phase. The model will be taught the weights that are used for image categorization or prediction.
For training, the model object can be called via a function called fit. One of the parameters to fit a function is the training dataset that was used to train the model. the data necessary to conduct validations during each trainingsession.
• Epochs that specify the frequency of model training.
• Callbacks, which are used to offer early stopping criteria to interrupt training when necessary. They are also used as model checkpoints to monitor any parameter and take action, such as saving the model, if validation accuracy improves relative to a previous training session.

RESULTS
The graphs below show the accuracy and loss for the DenseNet169 model during training and validation.



(a) Training accuracy and validation accuracy (b) train loss and validation loss

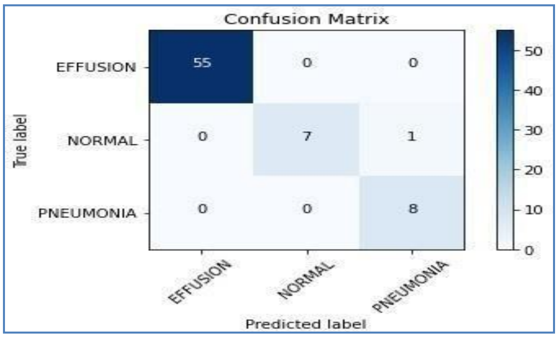
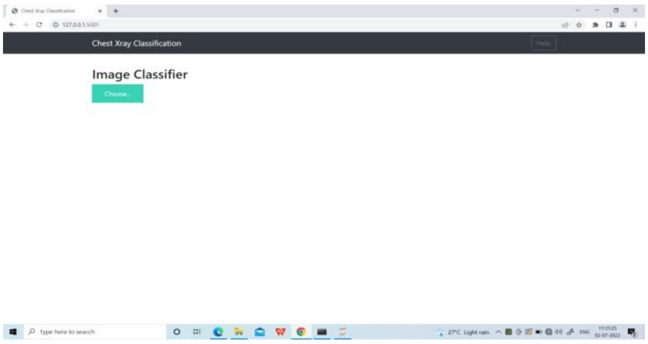
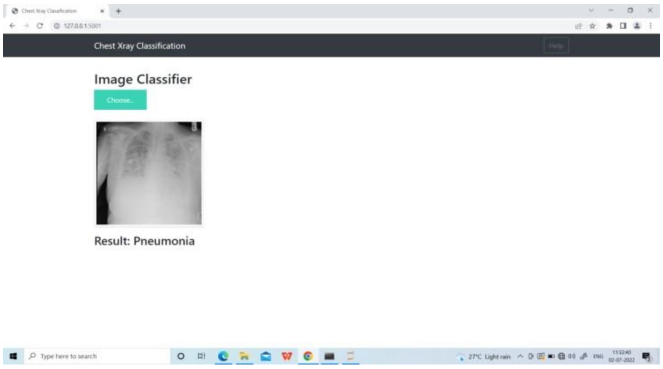


Figure above displays the confusion matrix plotted for the



DenseNet169.
Figure above displays a screenshot of the home page, which acts as the portal to the web application. To create the forecasts, the user has the option of uploading the chest x- ray image to the server. By selecting the pick file button on the webpage, the user can upload an image.



above image shows the result of prediction

CONCLUSION

The project we worked on was aimed at solving problems in healthcare brought about by a lack of radiologists and accessibility to medical facilities, especially in rural areas of the nation. Experienced radiologists are crucial for the quick and accurate identification of the numerous thoracic illnesses that could save the lives of innocent people. The project uses a system with artificial intelligence at its core to provide a strong fix for the issues. I developed a web application that consumers may use with almost no effort after installing on web servers. After a thorough analysis of ten previously trained application models employing transfer learning, DenseNet169 was chosen as the top model. 95.56 percent is a very good validation accuracy for this model.

SCOPE FOR FUTURE WORK:

The deep learning model we created for this project is used to classify the chest x-ray images into different groups. Only a tiny percentage of the dataset with images bearing a single target label was taken into account for the project because the dataset was unbalanced and there weren't many images with multiple label occurrences available for the training model. we can keep progressing toward multi-label classification by looking at targets with multiple labels for which we have a significant number of photographs in the dataset for the model to train. Using the project's findings as a springboard, the top three models with the best accuracy may be further enhanced. By using techniques like hyper parameter optimization to construct models that are optimized and deliver better results, we can improve our work.

REFERENCES

D. Varshni, K. Thakral, L. Agarwal, R. Nijhawan and A. Mittal, "Pneumonia Detection Using CNN based Feature Extraction," 2019 IEEE International Conference on Electrical, Computer and Communication Technologies (ICECCT), 2019, pp. 1-7, doi: 10.1109/ICECCT.2019.8869364

Hongyu Wang and Yong Xia," ChestNet: A Deep Neural Network for Classification of Thoracic Diseases on Chest Radiography", arXiv,2018, 1807.03058

Rahib H. Abiyev, Mohammad Khaleel Sallam Ma'aitah, "Deep Convolutional Neural Networks for Chest Diseases Detection", Journal of Healthcare Engineering, vol 2018, Article ID 4168538,11 pages,2018.https://doi.org/10.1155/2018/4168538

Pranav Rajpurkar, Jeremy Irvin, Kaylie Zhu, Brandon Yang and Hershel Mehta, Tony Duan, Daisy Ding, Aarti Bagul, Curtis Langlotz, Katie Shpanskaya, Matthew P. Lungren and Andrew Y. Ng," CheXNet: Radiologist-Level Pneumonia Detection on Chest X-Rays with Deep Learning", arXiv, 2017, 1711.05225

T. Rahman, M. E. H. Chowdhury, A. Khandakar, K. R. Islam, K. F. Islam, Z. B. Mahbub, M. A. Kadir, and S. Kashem, "Transfer Learning with Deep Convolutional Neural Network (CNN) for Pneumonia Detection Using Chest X- ray," Applied Sciences, vol. 10, no. 9, p. 3233, May 2020

Russakovsky, O., Deng, J., Su, H. et al. ImageNet Large Scale Visual Recognition Challenge. Int J Comput Vis 115,211–252 (2015). https://doi.org/10.1007/s11263-015-0816-y

Karen Simonyan and Andrew Zisserman," Very Deep Convolutional Networks for Large-Scale Image Recognition", arXiv,2015, 1409.1556

Kaiming He, Xiangyu Zhang, Shaoqing Ren and Jian Sun," Deep Residual Learning for Image Recognition", arXiv,2015, 1512.03385

Kaiming He, Xiangyu Zhang, Shaoqing Ren and Jian Sun," Identity Mappings in Deep Residual Networks", arXiv, 2016, 1603.05027

Christian Szegedy, Vincent Vanhoucke, Sergey Ioffe, Jonathon Shlens and Zbigniew Wojna," Rethinking the Inception Architecture for Computer Vision", arXiv, 2015,1512.00567

Christian Szegedy, Sergey Ioffe, Vincent Vanhoucke and Alex Alemi," Inception-v4, Inception-ResNet and the Impact of Residual Connections on Learning", arXiv,2016, 1602.07261

François Chollet, "Xception: Deep Learning with Depthwise Separable Convolutions", arXiv, 2017, 1610.02357

Gao Huang, Zhuang Liu, Laurens van der Maaten and Kilian Q. Weinberger," Densely Connected Convolutional Networks", arXiv,2018, 1608.06993

Barret Zoph, Vijay Vasudevan, Jonathon Shlens and Quoc V. Le," Learning Transferable Architectures for Scalable Image Recognition", arXiv, 2018, 1707.07012

Xiaosong Wang, Yifan Peng, Le Lu, Zhiyong Lu, Mohammadhadi Bagheri,Ronald M. Summers.ChestX-ray8: Hospital-scale Chest X-ray Database and Benchmarks on Weakly- Supervised Classification and Localization of Common Thorax Diseases, IEEE CVPR, pp. 3462-