Medical image classification and consultation By chatbot

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***Abstract*— Healthcare is an important and a very sensitive sector which should be properly handled by technology and more technical functionalities should be incorporated to help doctors and patients. The prime challenge that some patients faces is that their disease remains undetected and when intial detection of a disease is not done it sometimes turns into a big problem and if we see from the perspective of a doctor then due to time paucity doctor is not able to give consultation to each and every patient. This paper proposes a deep learning-based system that classifies medical image into diseases and further give information, cure, precaution to patients.Our system uses pretrained EfficientNetB0 and two EfficientNetB3. EfficientNetB3 predicts for brain tumor's from the brain mri image, EfficientNetB0 predicts for pneumonia from the chest Ct scan and finally another EfficientNetB3 predicts for lung cancer from lung histopathological images. After detection of the diseases our chatbot gives consultation, cure and information regarding the diseases .Results proved that the proposed model achieved the best accuracy of 96.8%,83.3 and 99.3 % for the brain mri , chest ct and lung histopathological datasets.Thus, the proposed model will help patients and doctors to enhance medical field and make it technology driven.**

Keywords—Histopathological, Deep learning, Pretrained ,Ct , EfficientNet ,Mri

I. INTRODUCTION

Medical care is for the health of people.In present times,there's a large quantity of medical data which should be used to facilitate healthcare industry [15].Advances in the field of science and technology,medical images should not be only used to read the image but should be used to analyze and predict the growing pattern from a deeper approach. Medical image classification is the study that combines technology and healthcare [14].

Image data is made up of pixels which relates to a physical object.Investigation of medical image data is still a problem with the point of view of obtaining insight values,analyzing and treatment of a specefic disease [14].There are several kind of medical scans which are used to detect various diseases which includes (1) CT scans-which are used to detect internal injuries after an accident,locating a tumor or cancer, (2) MRI(Magnetic Resonance Imaging)-which are used by clinicans to get insights on patients tensons and ligaments,organs or soft tisuues and inflammation of blood vessels, (3) Sonography used to check on fetal growth and development following that it is generally used to examine heart,gallbladder,liver,kidney,spine,etc,(4)VascularInterve nt-ional Radiography which combines CT scans,Ultrasounds and X ray's to guide nenign tumor therapis,remove kideny or gallbladder stones [16].

To detect and analyze any kind of medical image data there are three stages common which includes(1) feature extraction and representation, (2) feature selection that will be used for classification, and (3) feature and image classification.

Another model which is implied by healthcare sector are chatbots.In an uncomplicated terms chatbot is a program that understands human conversation and responds.Chatbots are generally created to copy the way a human would have behaved as a conversational partner.Chatbots are operated by artificial intelligence,machine learning and natural language processing.Chatbots are mainly classified into two types (1)Task oriented or declarative chatbots (2)Data driven and predictive or conversational chatbots.

Declarative chtabots are highly specefic which use rules, natural language processing and very little machine learning [16].Declarative chatbots works for single purpose programs which deals with performing one function whereas conversational chatbots are much interactive and customized. Conversational chatbots makes use of natural language understanding and processing and machine learning to learn while performing [16].Conversatiuonal chatbots put in predictive intelligence and anlytics to enable customization on the basis of user profiles and past user behavior.

As our research deals with the healthcare industry. So we will discuss more about healthcare related chatbots.These kind of chatbots operates on the rules of machine learning. In the recent years healthcare related chatbots have gained a lot of popularity.According to BIS research named Global Chatbots in Healthcare Market – Analysis and Forecast, 2019-2029,chatbots have accumilated $36.5 million in 2018 [18].

(HAVE TO DESCRIBE MORE ABOUT MEDICAL IMAGE CLASSIFICATION AND CHATBOTS WHEN METHODOLOGY IS IMPLIED.)

Our research is mainly classified into two main categories which firstly classifies medical images by neural networks and further gives cure or consulation to patients with the help of chatbots. Elaborately this research presents a complex deep learning model which takes input as a medical image like chest ct scans, brain mri & lung histopathological images as input from the patient and further classifies into patient which has a disease and patient which does not have a disease with the help of modified pretrained neural networks. So we have deployed 3 neural networks which have been trained for three different diseases. This research also compares the performance of pre trained models following that after predicting for a particular disease, chatbots comes into picture which answers the questions asked by patients for the disease and give consultation to the patient.

The organization of the paper is as follows: Literature Review is discussed in Section II. Data collection and preprocessing is given in Section III. The methodology is discussed in Section IV. Experimental setup, experiments and metrics are in Section V, Results and discussion are presented in Section VI and Conclusion is given in Section VII.

II. LITERATURE REVIEW

As the functionality of our model deals with predicting whether person has a disease or not and chatbots. So we had done a literature survey on medical image classification and chatbots used in the same field. Authors in [1] have highlighted the pros and cons of each deep learning models following they have also mentioned the reasons that what is stopping deep learning from taking over medical industry which includes unavailability of proper datasets, legal issues,etc.

To classify medical images, authors in [2] have presented a 3D Fully connected layer. Dataset have been taken from a research study with gastric cancer patients. Their proposed model achieved an accuracy of 89.3%.A review on medical image analysis by convolutional neural networks have been presented in [3].They have deeply discussed the topics such as segmentation, disease detection, computer aided diagnosis and it's retrieval. Authors have also mentioned sources that CNN's perform better that random forest, K nearest neighbour and SVM for body organ detection with an accuracy of 85.61%.

Authors in [4] have presented a system for medical image analysis using enhancement methods in deep learning.They have constructed a Deep CNN model. They have basically compared the performance of the model with augmented data and non-augmented data. They have collected the dataset of CT images of brain and achieved finally proved that model performs better with augmented data with an accuracy of 92.17%.In [5] author's have classified medical images by using unsupervised deep transfer feature learning.They have introduced a covolutional auto-encoder placed on top of AlexNet which is a well known pre trained model.They have consumed the output of the last convolution layer of the pre trained CNN and given as a input to the subsequent learning. Subfigure classification dataset has been consumed in this research and they have achieved an accuracy of 81.33%.

Authors in [6] have presented a work which classifies medical image for big data with the help of DCNN. They have relocated the features of GoogleNet which is a pretrained CNN by adding few layers in the last. Dataset has been collected online which consists of images with multiple classes of human body part for example chest,knee,etc.Their proposed method achieves an accuracy of 96%.In [7] author's have proposed a machine learning method for breast cancer detection. A Deep Neural Network with Support Value has been proposed which successfully extracts geometrical,entropy and textual features.Dataset consumed in this research was taken from M.G Cancer Hospital which had histopathology images samples.Ultimately their proposed model achieved an accuracy of 97.21% which outperforms the other methods such as Naïve bayes classifier,SVM,Bi-clustering,RCNN and Bidirectional RNN. Authors in [8] have presented a system for early lung cancer diagnostic biomarker discovery by ML methods. They have compared the performance of 6 ML techniques:Naïvebayes,SVM,AdaBoost,RandomForest,KNN and Neural Networks. Dataset has been consumed from Hubei Taihe hospital. Ultimately they have applied logistic regression to increase the accuracy to 92.9% and concluded that there are 6 metabolic biomarkers which plays a role in early detection of lung cancer. Chatbot for healthcare system using Artificial Intelligence have been presented in [9] which helps the patients regarding minor health information. N-gram and TF-IDF have been used for extracting keywords from the question asked by the patients.

Authors of [10] had built a Dermatobot which is an image processing chatbot for detecting the disease and providing cure of skin diseases.Initially the model predicts the top 5 most probable disease which gets compared to the symptoms the patients enter.Following that,class of the disease gets predicted whoose similarity is 100.Ultimatley treatment related answers have been given to the user which are connected to the database.EfficientNet B4 model has been consumed for image classification and Universal Sentence Encoder for encoding the symptoms entered.Dataset was consumed by Google and Bing images on which they achieved an accuracy of 92% for image classication.In [11] authors have presented a system LINE Bot for automatic Rice Disease detection from Rice paddy Images operated by a chatbot. Rice Disease detection was done by YOLOv3 and the questions related to rice diseases and solutions were answered by LINE Bot which is operated by the Rice disease specialists who sends the response.Rice Dataset has been developed by clicking pictures from the fiels which were further crosschecked by specialists and they achieved an accuracy of 95.6%. –2021 Authors in [12] have presented a medibot which is a conversational chatbot which detects the disease when the patient enters it's symptoms by just simply matching pattern in the snippets. Model was trained by SVM,KNN and Naïve bayes among which SVM performed the best with the accuracy of 94.6%.An user friendly chatbot have been developed in [13] to detect generic diseases and specifically diabetes.Chatbot basically converses with patients with the help of Natural Language Understanding for providing personalized detection by general health dataset following that chatbot has been specialized for Diabetes detection using Pima diabetes Indian dataset for providing cure. React UI was used for front end. Ensemble learning performed the best with 84.2% when compaired to general ML classification algorithms.

It could be observed from the literature that there is no such complex model which contains three neural networks predicting for three different diseases in which each neural network has been specifically trained for one disease following that consultation & cure will be given by chatbot for each disease by maintaining databases.

III. DATASET

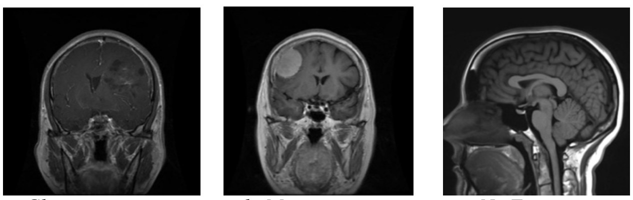
A. Data Collection

To deploy the model, three publicly available datasets have been consumed. The first dataset is the Brain MRI dataset [20] which contains Brain MRI images. The second dataset is Chest CT scan dataset [21] which contains images of chest CT scans. The third dataset is Lung Cancer images [22] which contains histopathological images of lungs.

The Brain MRI dataset consisted of 7022 of human brain MRI images which are further divided into 4 classes in which 3 classes are types of brain tumor and 1 class consists of images with no tumor. Classes are as follows: Glioma(class 1),Meningioma(class 2),No tumor(class 3) & Pituitary(class 4).Table 1 shows the number of images in each class. The dataset has been split in the ratio 80:10:10 for training, testing & validation.

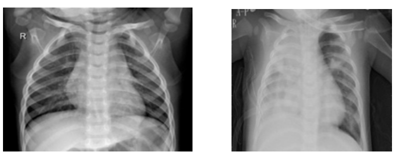
The Chest CT scan dataset consisted of 5856 of human Chest CT images which are further divided into 2 classes. Classes are as follows: Normal(class 1) & Pneumonia (class 2).Table 2 shows the number of images in each class. The dataset has been split in the ratio 80:20 for training & testing.

The Lung Cancer dataset consisted of 9024 histopathological images of lungs which are further divided into 3 classes in which 2 of them contains cancerous histopathological images and other class contains normal images. The division is as follows: Lung adenocarcinoma (class 1), Lung squamous cell carcinoma(class 2) & Lung benign tissue(class 3).Table 3 shows the number of images in each class. The dataset has been split in the ratio 70:15:15 for training, testing & validation.



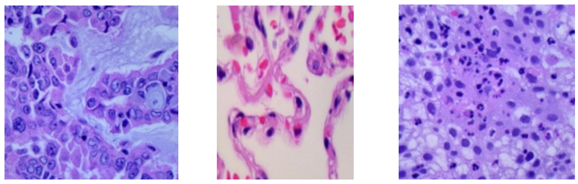
a .Glioma *b. Meningioma* *c.No Tumor*

Fig. 1. Sample images from Brain MRI dataset



a.Normal *b.Pneumonia*

Fig.2. Sample images from Chest CT scan dataset.



a.Adenocarnima *b. Benign* *c. Squamous*

Fig.3. Sample images from Lung Cancer dataset.

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TABLE I. BRAIN MRI DATASET-DISTRIBUTION OF IMAGES

Class	**No of Images**
Glioma	1621
Meningioma	1644
No Tumor	1999
Pituitary	1757

TABLE II. CHEST CT SCAN DATASET-DISTRIBUTION OF IMAGES

Class	**No of Images**
Normal	1584
Pneumonia	4272

TABLE III. LUNG CANCER DATASET-DISTRIBUTION OF IMAGES

Class	**No of Images**
Lung Adenocarcinoma	3006
Lung Squamous carcinoma	3008
Lung benign tissue	3006

B. Data Preprocessing

Preprocessing is the essential stage for any image processing system. All the three datasets which were consumed in this paper were already preprocessed. We only resized the images to (224,224) following that we changed the number of images in each class which would be best suitable for our model.

IV. METHODOLOGY

This work presents a complex deep learning model which will predict whether the patient has a disease or not and ultimately it will provide consultation & cure to patients. Model has been divided into two major steps. First step is to classify whether the person has a disease or not. As we are predicting for three different medical image types: MRI,CT scans and histopathological images. So three different neural networks have been trained. Such that one neural network has been trained for one type of medical image. Three neural networks have been used because medical imaging is a very sensitive topic and no such kind of error is acceptable. The pretrained model EfficientNetB3 has been used for brain mri,EfficientNetB0 for chest CT scan and EfficientNetB3 for lung histopathological images. Following that experiments have been conducted on each dataset with four other pretrained models which will be discussed in section V but we have discussed about the details of only EfficientNetB0 & B3 because they obtained the best results among other pretrained models. Training and testing has been conducted on each of the model for three datasets. After completion of the training and testing phase, program starts by asking the user that which kind of medical image will the user input, Whichever type of medical image is selected by user, control will be given to that neural network which is trained on that medical image. After predicting for that medical image,Our second step comes into picture which gives consultation and cure to the patients by chatbots. Our designed chatbot contains all the necessary answers which patients generally ask by doctors. It is a rule based Chatbot which operates on rules and intents provided to converse with patients .Fig. 1 shows the process of our model.

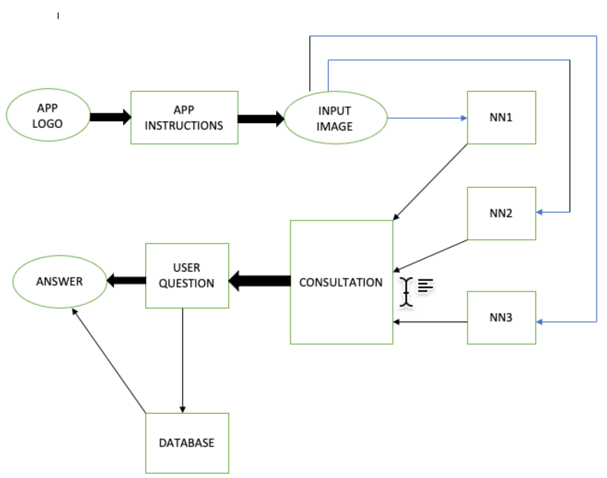


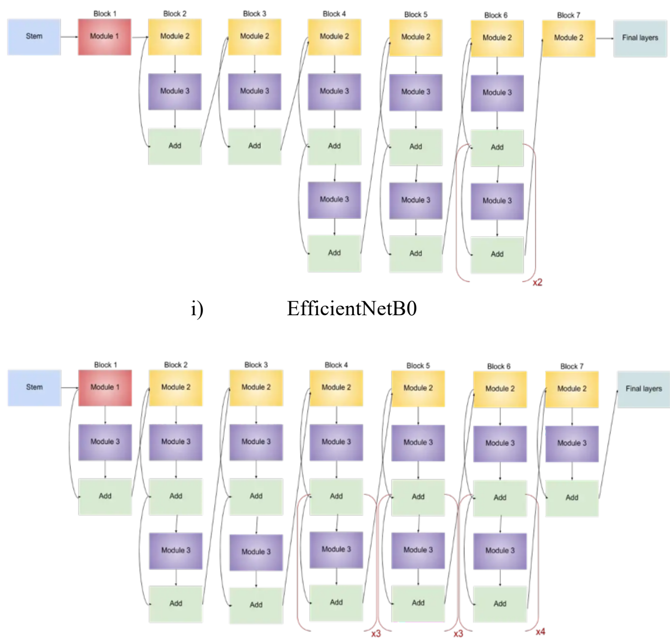
Fig.4. Process of the model

A. Medical Image Classification

As mentioned earlier, the brain mri classification uses pretrained EfficientNetB3 whereas EfficientNetB0 for chest CT scan and finally EfficientNetB3 has been used for lung histopathological images. A pretrained model can be also called a saved network which has already been gone through training on vast datasets and respective weights have been saved. Transfer learning is a way in which pretrained models can be applied to other datasets and could be used as a general or a specific problem. This section explains about those EfficientNets which are used in this research in detail.

When different models were built which concentrated on computational efficiency or performance, the EfficientNet was developed to solve both these issues [23]. EfficientNet was proposed in 2019 [24] which was powered by appropriate scaling method and AutoML framework.The baseline EfficientNetB0 is 29 MB with 5.2 million parameters and EfficientNetB3 48 MB with 12.3 million parameters [25]. EfficientNet is a deep CNN architecture and appropriate method that uniformly scales depth/width/resolution using a compound coefficient. For example, if 2^N times more computational resources have to used then simply network depth,width and image size can be increased by a^N,b^N & y^N where a, b & c are determined by a small grid search [24].

The base EfficientNet-B0 works upon the inverted Bottleneck residual blocks of MobileNetV2 with excitation and squeezing blocks. The stem after which all the experimenting with the architecture starts is common in eight models of EfficientNets from b0 to b7.Following that each contains 7 blocks which has different number of sub-blocks which increases from EfficientNetB0 to EfficientNetB7.Fig. 5 shows the architecture of EfficientNetB0 & B3.The difference is only that number of channels which affects count of parameters.



i) EfficientNetB0

ii) EfficientNetB3

Fig.5. Architecture of EfficientNetB0 & B3

B. Model Training

The EfficientNetB0 & B3 models pretrained on ImageNet were used in this work. In order to finetune the model on the brain mri dataset EfficientNetB3 was used whereas for chest ct scan dataset EfficientNetB0 and finally for lung histopathological dataset EfficientNetB3 was used. For the classification of three tasks the last 40 layers of the each of the models were set as trainable while the other initial layers of the model were frozen. Two fully connected dense layers were added on top of the model. The first dense layer had 1024 nodes, ReLu activation function and 0.2 dropout. The second dense layer had $\mathbf{X}$ nodes and softmax activation function. $\mathbf{X}$ denotes the number of classes. For the brain mri classification task, $\mathbf{X}$ was set as 4 whereas for chest ct scan classification $\mathbf{X}$ was set as 2 and finally for lung histopathological image classification $\mathbf{X}$ was set as 4.Adam optimizer was used as it is faster and the learning rate was set as 0.0001. The model was trained for 70 epochs for each of the classification.

C. *Chatbot*

As mentioned our complex deep learning model also includes consultation through chatbots. So to deploy this functionality we have developed a basic rule base chatbots. Rule based chatbots are uncomplicated. They are given with a database and rules are initialized which assists them to give suitable answer to the query [28].

So to create our rule based chatbot we have started by importing basic libraries like random, re, etc following that we have created several intents like Pneumonia, No pneumonia, Glioma, Meningioma, Pituitary, No brain tumor, Lung squamous cell, Lung adenocarcinoma, Lung Benign tissue, etc. We have incorporated each of the intents with all the necessary information for the particular class. Information include precaution, cure, symptoms and emergency. Chatbot starts by giving a greeting message to user and whatever user asks ,depending on the keyword, it gives control to that intent and answers the question accordingly. Fig 6 shows the sample of the chatbot conversation when the user asks about pneumonia.

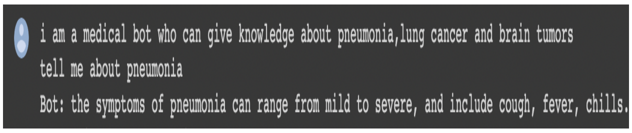


Fig.6. chatbot conversation when the user asks about Pneumonia.

V. IMPEMENTATION, EXPERIMENTS AND METRICS

A. *Implementation*

Our proposed model was implemented using Tensorflow with Python 3.7.13 and Google Colaboratory(CoLab) Pro which is an interactive Jupyter development notebook. In addition numpy, scikit, pandas ,warnings ,glob ,resize ,glob, os ,sklearn ,etc were used. A Tesla T4 GPU was used was used to run the programs.

B. *Experiments Conducted*

Experiments were conducted on 4 other pretrained CNNs to identify the best model for brain mri classification,chest ct classification and lung histopathological image classification.The pretrained models used in the experiments are:EfficientNetB0 [24],EffecientNetB1[24], EffecientNetB2[24],Xception [26] and InceptionV3 [27] .

C. *Metrics*

All the models are evaluated using the following metrics.

*a) Accuracy:*It is calculated by dividing the number of correct predictions by the total number of predictions and is given by equation 1.

$$\text{Accuracy} = \frac{\text{Correct predictions}}{\text{Total predictions}} \quad (1)$$

*b) Precision:*It is defined as the number of instances that are true positives over all the examples that were predicted to fall into a particular class and is given by equation 2.

$$\text{Precision} = \frac{\text{True positives}}{\text{True positives} + \text{False positives}} \quad (2)$$

*c) Recall:*It is defined as the number of instances that are true positives over all the examples that truly belong to a particular class and is given by equation 3.

$$Recall = \frac{True\ positives}{True\ positives + False\ negatives} \quad (3)$$

*d) F1 score:*It combines both precision and recall into a single measure and is given by equation 4.

$$F1\ score = \frac{2 * Precission * Recall}{Precision + Recall} \quad (4)$$

VI. RESULTS AND DISCUSSION

A. *Performnce Analysis Of Brain Mri Classification*

Table IV shows the accuracy, precision, recall and F1 score of the various models for the brain mri classification task. It could be seen from the table that the EfficientNetB3 model obtained the best testing accuracy, precision, recall and F1 score of 0.968, 0.96, 0.96 and 0.96 respectively. The precision,recall and F1 score achieved by EfficientnetB0 and EfficientNetB1 was same which was 0.96 but testing accuracy by EfficientNetB0 was 0.962 and EfficientNetB1 was 0.966 following that Xception achieved an accuracy of 0.960 with precision,recall and F1 score of 0.95.While the worst results were obtained by InceptionV3 with an accuracy of 0.942.

B. *Performnce Analysis Of Chest Ct Classification*

Table V shows the accuracy, precision, recall and F1 score of the various models for the chest ct classification task. It could be seen from the table that the EfficientNetB0 model obtained the best testing accuracy, precision, recall and F1 score of 0.833, 0.76, 0.88 and 0.81 respectively. The Xception model also performed good with an accuracy of

0.825 with precision, recall and F1 score of 0.76, 0.88 & 0.81.InceptionV3 achieved an accuracy of 0.807 with precision, recall and F1 score of 0.74,0.85 and 0.79 respectively.EfficientNetB3 achieved an accuracy of 0.806 while the worst results were obtained by EfficientNet1 with an accuracy of 0.778.

C. Performnce Analysis Of Lung Histopathological Classification

Table VII shows the accuracy, precision, recall and F1 score of the various models for the lung histopathological classification task. It could be seen from the table that the EfficientNetB3 model obtained the best testing accuracy of 0.993 with precision, recall and F1 score of 0.99 respectively. The EfficientNetB0 model also performed good with an accuracy of 0.991 with precision, recall and F1 score of 0.99, 0.98 & 0.98. EfficientNetB1 achieved an accuracy of 0.990 with precision, recall and F1 score of 0.98 respectively. Xception achieved an accuracy of 0.987 while the worst results were obtained by InceptionV3 with an accuracy of 0.976.

TABLE IV. RESULTS FOR BRAIN MRI CLASSIFICATION

Models	Accuracy	Precision	Recall	F1 score
EffcientNetB0	0.962	0.96	0.96	0.96
EfficientNetB1	0.966	0.96	0.96	0.96
EfficientNetB3	0.968	0.96	0.96	0.96
InceptionV3	0.942	0.94	0.94	0.94
Xception	0.960	0.95	0.95	0.95

TABLE V. RESULTS FOR CHEST CT CLASSIFICATION

Models	Accuracy	Precision	Recall	F1 score
EffcientNetB0	**0.833**	0.76	0.88	0.81
EfficientNetB1	0.778	0.86	0.87	0.86
EfficientNetB3	0.806	0.73	0.87	0.79
InceptionV3	0.807	0.74	0.85	0.79
Xception	0.825	0.76	0.88	0.81

TABLE V. RESULTS FOR LUNG HISTO. CLASSIFICATION

Models	Accuracy	Precision	Recall	F1 score
EffcientNetB0	0.991	0.99	0.98	0.98
EfficientNetB1	0.990	0.98	0.98	0.98
EfficientNetB3	0.993	0.99	0.99	0.99
InceptionV3	0.976	0.97	0.97	0.97
Xception	0.987	0.98	0.98	0.98

VII. CONCLUSION

This work introduced a complex model which could classify medical images into diseases. This was achieved by the brain tumor, chest ct and lung histopathological classification sub-systems which used a pretrained EfficientNetB0 and B3 model. Experimental results show that the model is able to provide appropriate recommendations for query input images. We have also incorporated a basic chatbot to give information ,cure and precaution for the detected disease. The proposed model can act as an assistant for the patients who struggle to go to hospital and are sometimes left in a doubt for their diseases. In future, the model could be extended by enhancing the knowledge of the chatbot and make it more powerful following that more disease could be included which would make this model a biggest medical image classifier bot. Proposed model could also be incorporated inro a medical software and application which could help doctors and patients.

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