Project Report

Medical Image Reader Powered by Artificial Intelligence

by

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Abstract

As a radiologist has to check a vast number of reports alone, also some countries do not have enough radiologists as per the demand. According to statistics, a very few radiologists are intending to apply artificial intelligence in preparing a report summary by analyzing the data [12]. Medical imaging produces visual representations of areas inside the human body in order to diagnose medical problems and monitor the treatment. Root causes of almost every disease, illness and medical issue arise inside the body. Hence, since its first discovery in 1895, [1] medical imaging has left a massive impact on public health. When the diagnosis is completed, a radiologist analyzes the results and sug- gests the most appropriate treatment for the patient. Therefore, the faster and more accurate the diagnostic process is, the better the treatment will be. Our proposed project aims towards an interface model using Deep Learning (DL) techniques so that the diagnosis of a medical issue can become faster, easier and more precise. The goal of this research is to find the best suited models to classify different types of medical images, to extract data from an image in order to analyze the date and detect any existence of a medical issue with the best accuracy possible. Neural Net- work is one of the most used DL techniques which plays a vital role in analyzing medical images. The initial outcome of the research is some existing modified AI- based models which are already giving accurate results in detecting different kinds of diseases by analyzing different types of medical images, for example, CheXNet for detecting thoracic diseases [5], CoroNet for identifying COVID-19 [9] etc. These models are combinations of a number of various architectures, such as: SVM, Trans- fer learning, VGG, Inception, DenseNet, CapsNet, ResNet etc. At the conclusion of our research, we try to find and merge these models with the best accuracy in order to identify particular medical issues by analyzing a medical image. Keywords: Medical Imaging, Deep Learning, Neural Network, CheXNet, Coronet, VGG, Inception, DenseNet, CapsNet.

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Chapter 1

Introduction

1.1 Medical Imaging and Deep Learning

Modern technologies have shadowed every corner of the world. Each and every fundamental of human life including the medical sector is now deeply connected with the new age of technology. Medical sector consists of three broad parts- diagnosis, analysis and treatment. Most diseases and illnesses start their journey from the inner side of the human body. Sometimes the cause of illness can be diagnosed by checking some outer body conditions, such as: high temperature of the body is a symptom of fever, a yellow tinge to the skin and the whites of the eyes can be symptoms for Jaundice etc. Nevertheless, there are enormous numbers of medical conditions which need the assistance of technologies to be analyzed, explained and treated. Notably, Medical Imaging is one of the very common and highly used modern technologies in the diagnosis part. In general, one or more medical imaging procedures are performed on a patient's body as per the request of a Radiologist. Radiologists are trained to diagnose diseases or injuries or the causes for an illness by analyzing the outputs of the procedures. These outputs are, in fact, images captured on films which contain the information regarding the inner body of the patient. Most common types of medical images are X-ray, Magnetic Resonance Imaging (MRI), Computerized Tomography (CT scan), Ultrasonography, Endoscopy, Tactile Imaging etc. Each of these imaging techniques can help in diagnosis of a wide range of medical conditions. Following is a brief idea about three most common medical images and their scopes of usage:

X-Ray	Thoracic diseases; Bone fractures; Arthritis; Osteoporosis; Infections; Breast cancer; Swallowed items; Digestive tract problems
CT Scan	Injuries from trauma; Bone fractures; Tumors and Cancers; Vascular disease; Heart disease
MRI	Aneurysms; Multiple Sclerosis (MS); Stroke; Spinal Cord disorders; Tumors; Blood vessel issues; Joint or Tendon injuries

In some cases, one procedure alone cannot explain the existence of a disease or abnormality of health. Then, multiple types of diagnostic procedures are performed and by analyzing all the generated medical images, radiologists may be able to 2 diagnose the condition. Availability, knowledge and experience of the radiologists

play a key role here in the diagnosis process. Another component in this modern age of technology is Deep Learning (DL), a sub- set of Artificial Intelligence (AI). DL has a huge impact upon many sectors of human life as well. Common DL applications are Virtual Assistants (Siri, Alexa, Cortana etc.), Vision for Autonomous cars (Tesla), Facial Recognition, Object Detection and so on. Following is a broad picture of the difference in work-flows between Machine Learning and Deep Learning:
Among a number of deep learning algorithms, some are very popular and being used in different scopes, e.g: KNN (K-nearest neighbor) method, Convolutional Neural Network (CNN), Deep Neural network (DNN), Generative Adversarial Network (GAN),Restricted Boltzmann Machine(RBM) etc. These algorithms are used in classification, segmentation, processing or analyzing data. Focusing on the medical sector, the accuracy of analyzing medical data by these algorithms is remarkable. More specifically, these data driven classifiers have revolutionized medical imaging fields namely: Image segmentation, computer-aided diagnosis systems, content-based image retrieval image annotation etc. With better technologies, medical data has been more accessible than in the past. Hence, innovating advanced algorithms can take the development of the medical sector to a greater height of success. Con- 3 sequently, the synergic efforts of data scientists and radiologists would revolutionize the medical sector using the data driven classifiers.

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Chapter 2

Problem Statement

According to a research in 2014[2], approximately 12 million people are misdiagnosed annually in the United States; among them, an estimated 40,000 to 80,000 cases lead to death. Almost no disease can be diagnosed without medical imaging procedures let alone starting treatment. There are some factors which don't always come under the light during a medical diagnostic process. As we know, Radiologists are the first to diagnose the condition of an inner body by analyzing a medical image. There are specialized doctors to confirm that. Nevertheless, the availability, knowledge and experience of the radiologists play a major role in the diagnosis. Some countries may not have specialized radiologists, on the other hand, the specialized doctor may not be aware of a disease which may be common in a very distant country. Additionally, there are a lot of emergency cases where the patient needs treatment as early as possible to survive, however, because of unavailability of specialized persons, the diagnosis process becomes lengthy. Hence, misdiagnosis, unavailability of radiologists, low experience of the doctor sometimes lead a patient to even a worse case possible. In the encounter of these problems, the manpower needs a good amount of time to gain experience. On top of that, to eradicate the issue of unavailability, governments of each country should focus on the radiology department of the hospitals so that more radiologists are hired having a good number of scopes of practice. Still then, there remains many options of errors to be occurred and misdiagnosis to take place. Therefore, the medical sector needs an alternative system which can analyze and identify the existence of a disease or a cause of illness just by reading a medical image as precisely as possible.

Chapter 3

Research Objective

In the research, we have tried to find as many CNN models as possible in order to identify a number of medical conditions. The main objective of this research is to gather the models for diagnosis of different kinds of diseases. The remaining objectives are as following:

- To develop the final model using required resources, specially high powered GPU.

- To develop the final dataset consisting of all the diseases that we aim to reach for building the system.

- To apply data balancing techniques like data augmentation, smote etc on the full dataset in order to get a balanced dataset and reduce overfitting.

- To use image enhancing techniques like CLAHE, AHE, histogram equalization etc to increase the dataset for a better accuracy.

- To apply hyperparameter tuning for a better model with the optimum performance.

- To develop a user-friendly interface.

- To compare our model with pre pre-trained models to clarify our experiment.

Chapter 4

Detailed Literature Review

Since the introduction of OCT, many academics have been intrigued by its capacity to properly depict the retinal tissue layer by layer and have pondered how it can further neurological research. Previous research has suggested a connection between neurodegenerative disorders and retinal layer atrophy. These scientists experimented with various techniques in various contexts to show how neurological processes in the brain may also be seen in the retina. Overviews of a few of these investigations are provided in the section that follows.

According to [11], An Efficient CNN Model for COVID-19 Disease Detection Based on X-Ray Image Analysis and Classification, by Aijaz Ahmad Reshi, et al., is published in Complexity Volume 2021 (2021). The proposed CNN model has been tested in two scenarios using 100 X-ray images of the original processed dataset. The study used 450 X-ray images that have been ripped and rotated by 90°angle to get additional 90 images. The proposed CNN model consists of 38 layers of which 6 are convolutional (Conv2D), 6 max-pooling layers, 6 dropout layers, and 8 activation function layers. The proposed CNN model could be applied to diagnosis using X-ray images for the current COVID-19 diagnosis using MRI and CT scans. SVC has been used with the linear kernel which is best for binary class classification. The primary dataset was very limited in size and also imbalanced in terms of class distribution.

According to the research team [8], This study has employed five models to classify MR images of the brain into normal, cerebrovascular, neoplastic, inflammatory, and neurodegenerative classes. Each pre-trained model was trained 5 times and the classification accuracy was calculated for each training. They used 80% of the dataset for training and 20% for validation sets. The lowest performance is obtained for the AlexNet model (80.11% $\pm$ 3) and the highest is for the ResNet-50 model (95.23% $\pm$ 0.6).

The research paper [10] inferred that Alzheimer's disease is a chronic, irreversible brain illness that gradually erodes memory and cognitive abilities. To enhance the method for detecting Alzheimer's disease, machine learning techniques are applied. The 12-layer CNN model in this study makes the most significant contribution, outperforming all other CNN models that have been published on this dataset with an accuracy of 97.75%. For binary classification and diagnosis of Alzheimer's disease, a 12-layer CNN architecture has outperformed all others with an accuracy of 97.75%. To get around the aforementioned restrictions, this research suggests a model. Comparing their suggested model's performance to that of current CNN models demonstrates how much better their proposed model is than the ones that are now in use. Figures show a block diagram of their suggested approach.1 that displays the entire procedure for the suggested method. Their suggested 12-layer CNN model in this section for the identification and categorization of Alzheimer's disease in brain MRI images. Sigmoid and ReLU activation functions, as well as Conv2D, Maxpooling2D, and a Leaky ReLU activation function have all been employed. The following are the formulas for accuracy, f1-score, and precision. Image resizing and Image denoising were two data-preprocessing techniques that were used. On the OASIS dataset, the accuracy of their suggested CNN model was the greatest.

The research work [3] proposed that different types of lung disorders are referred to as interstitial lung disease. The suggested approach combines a local binary pattern extractor with 7 layers of CNN. The major tools for classifying colored images are AlexNet and CNNs. CNN initially extracts features before training an ANN classifier to reduce classification error. CNNs for the identification of aberrant or normal lung disease is the focus of this study (LDL). The system has five stages: training, picture preprocessing, segmentation, feature extraction, and classification utilizing local binary patterns and CNN (LBP). LBP has primarily been used to categorize textures. It can be applied in real-time scenarios thanks to its computational simplicity. Since lungs typically come in a variety of sizes, pre-processing was required to extract lung features from CT scan pictures. To locate the lung ROI, an image segmentation method is used. Next, the lung feature is extracted using a convolutional neural network (CNN) or support vector machine (SVM), as appropriate. When employing SVM instead of CNN, the system's accuracy decreases to 86.66% from 94%. They can conclude that CNN is more accurate. On a dataset of 30 CT scan images utilizing CNN, the suggested system demonstrated worthy results, giving us an accuracy of 87%. The research paper [14] emphasizes that traditional

diagnosis uses an unreliable RT-PCR assay on samples from the nose and throat. These patients can be identified from chest X-rays and CT scan pictures using AI-based models. These models' performance for categorizing diseases, however, is not as good as that of conventional CNN models. A publicly accessible collection of CT scans and X-ray pictures was used in this study. SqueezeNet, ResNet50, and ResNet18 were all employed for classification. They discovered that several of the photographs had low quality after manually inspecting them. To select the parameters for a CNN model, the Adam optimizer combines the RMSprop and momentum heuristics. 50 photos were incorrectly labeled as COVID, while 723 non-COVID images were accurately identified by the suggested CNN model. A 32-filter initial convolution layer is followed by 19 residual bottleneck layers in MobileNetV2. The InceptionV3 model is more computationally efficient. Deep neural networks have been proposed by a study team as a computer-aided method for the detection of Covid-19 from chest X-ray pictures. The research paper[7] asserts that CADx is

more potent than feature-based CADx, which calls for an image extractor. Radiologists employ computer-aided diagnostic (CAD) technologies to help in lung disease diagnosis. In this study, they create a CADx that uses images to identify and categorize lung anomalies. The domains of speech and vision have seen a significant improvement in pattern recognition because of deep learning. With the aid of CNN, they have created an image-based CADe for the identification of lung abnormalities such as lung nodules and lung illnesses. They employed a variety of imaging techniques on CT scans from 163 patients with lung nodule cases and 372 patients with diffuse lung illnesses. The ImageNet dataset, which contains 1.2 million training images and 1,000 item categories, was utilized to train a pre-trained CNN model. In order to obtain nodular patterns for lung disease, they eight times rotated and reflected picture data. In order to prevent results from being biased, randomization was used. The object detection framework R-CNN focuses primarily on areas of an image that are likely to contain an item. Using a selective search, it generates bounding boxes or region proposals. R-mean CNN's accuracy for classifying benign and malignant lung nodules was 95% for training data. The mean accuracy for five lung disease patterns (CON, EMP, GGO, HON, and NOR) was 81.1% without data augmentation and 84.7% with it, with a 99.4% accuracy rate for patients with malignant or non-malignant disease. They trained a computer program to recognize different types of lung nodules and diffuse lung disease patterns using CADe.Due to a lack of training nodules, CADe was unable to detect various types of nodules, including those adhering to the mediastinum and chest wall. It is common practice to utilize computer-aided classification (CAD) to recognize several types of pulmonary abnormalities, including diffuse lung illnesses and lung nodules.

According to the research paper [13], Their project develops smartphone applications for illness real-time diagnostics using machine learning algorithms. Machine learning is used to handle a variety of challenging problems involving both people and machines (ML). According to one study, an algorithm should be used to carry out local and global updates, which are crucial to the learning process. Machine learning uses artificial neural networks to track daily activity and detect falls. The clinical steps for controlling diabetes in this demographic have been identified because diabetes is more common in older people. After the data was cleansed, 80 more rows were added to the COVID-19 dataset, which only contains the information of patients who tested positive for drug or alcohol addiction. Separated into two groups were countries with more than 10,000 instances and those with fewer than 1,000. The objective of the project is to develop a theoretical model of AI prediction that can be easily implemented in real-time applications. A heat map was made to determine the importance of each study's data characteristic. The data is stored in a firebase database, and the coefficients and intercepts are stored in the firebase real-time database. For early COVID-19, diabetes, and cardiac patient screening, the recommended model might be helpful. It can also be helpful for other applications like handwriting recognition and image filtering. Research paper[1] portrays that

diabetes is more prevalent in older folks, and an effort has been made to identify the clinical steps for managing diabetes in this population. The COVID-19 dataset, which solely contains the details of patients who tested positive for drug or alcohol addiction, was expanded by 80 additional rows after the data was cleaned. Two sets of nations, one with more than 10,000 cases and the other with fewer than 1,000, were separated. The research's goal is to create a theoretical model of prediction using AI and to make it feasible to deploy the models in real-time applications without many limitations. To gauge the significance of each study's data characteristic, a heat map was created. The coefficients and intercepts are kept in the firebase real-time database, and the data is kept in a firebase database. By doing so, they can modify the parameters as the dataset expands and the training quality rises. The suggested model may be useful for early COVID-19, diabetes, and cardiac patient screening. Additionally, it can be useful for other applications like image filtering and handwriting recognition. The research paper's [6] aim is to bring the medi-

cal and artificial intelligence fields together so that people understand how AI and medicine can work together. Brain Tumor Cancer Module is a brain tumor scale that can be combined with other questionnaires. Brain invasion is added to the list of requirements for atypical meningioma. Suggested MRI image classification has an accuracy of 96.23 percent and a sensitivity of 92.3 percent. Data security and privacy must be considered as well as the impact of imperfect data on performance and efficiency. The use of cloud computing for training may be able to solve the difficulty of dealing with large image sizes. Some of the key papers in the field of machine learning are published in the International Jtheirnal of Innovative Technology and Exploring Engineering (IJITEE). By the research team[4] The ImageNet

classification challenge has played a major role in advancing state-of-the-art computer vision. VGG processes one image in a fifth of a second, making it a less likely contender in real-time applications. AlexNet shows a speed up of roughly3$\times$ going from the batch of 1 to 64 images. Their detection system is Faster R-CNN [32] with the improvements in Table 9, using ResNet-101. They achieve 85.6% mAP on PASCAL VOC 2007 and 83.8% on PASCAL 2012.

In 2017, Pranav Rajpurkar Et al.[5] introduced us with an algorithm called CheXNet which is an algorithm that can detect Pneumonia from chest X-rays at a better level than practicing radiologists. Authors used a dataset called ChestX ray14 dataset. It contains 112,280 front-view chest X-ray of 30,805 different patients; all labeled up to 14 different thoracic diseases including pneumonia. For this experiment, among the 14 labels, Pneumonia has been selected as a positive label and all the other ones are used as negative ones. Dataset was splitted into training dataset(98637 images) , test dataset (420 images), validation (6351 images) where there is no overlapping patient in these sets of data. Firstly, the images are down-scaled to 224x224 and normalized based on the ImageNet Training set.Then, training data is augmented with random horizontal flipping. Pneumonia detection is a binary classification problem, hence, 121- layered Dense Convolutional Network, shortly named as DenseNet, is trained on the dataset. Briefly, it optimizes the deeper networks to generate better outputs (check the link in the keyword for better understanding). Four practicing radiologists (with experience of 4,7,25 and 28 years) independently labeled the test set. Authors used the same dataset ChestX-ray14. At first, the PNG images were rescaled into 1024x1024. Each image had one/multiple labels. These labels were extracted from the radiological reports using Natural Language Processing (NLP). Then, the dataset was split into training and test subsets (80% : 20%). In the classification branch, the ResNet-152 model has been used since it is pre-trained in the ImageNet dataset. This model consists of 152 learnable layers. In order to adapt this model to their project, the softmax layer was removed and the last fully connected layer was replaced with a layer of 14 neurons; each using the sigmoid activation. Outputs of these 14 neurons are defined as Label Prediction Vectors. In the attention branch, the relationship between the labels and regions of abnormalities are derived using the analysis of learned feature maps. For this, the input of this branch is the second last residual output from the classification branch. Finally, the output from the attention branch is defined as the Label Confidence Vector. Authors first trained the classification branch (all parameters fixed), then trained the attention branch. Each training process was designed in a way so that the cross-entropy loss can be minimized. The authors of the paper found that their proposed model achieved a better average per-class AUC than the other deep learning methods in diagnosing each of 14 thorax diseases.

Chapter 5

Methods and Algorithms

The main motive of our study was to find the appropriate models for each disease that we want our system to detect. Although our target is to build a system which will be able to detect diseases for every major organ in the human body, we have preliminarily gathered ideas regarding models for diseases of lungs, brain, knees and chest. Thus, we tried to cover some common but crucial diseases which require medical images to be diagnosed. The gathered analysis of our research is as follows:

Ref.	Year	Proposed Model Genre	Features	Disease (Medical Image)
[1]	2021	CNN	38-layered model including 6 convolutional, 6 max-pooling, 6 dropout layers and 8 activation functions.	COVID-19 (X-ray)
[2]	2019	CNN	Classifies image into five classes	Brain Diseases (MRI)
[3]	2020	CNN	12-layered model including Conv2D, Maxpooling2D, and a Leaky ReLU activation function	Alzheimer's Disease (MRI)
[4]	2018	CNN	7-layered model with the support of AlexNet	Interstitial Lung Diseases (CT image)
[5]	2021	CNN	SqueezeNet, ResNet50, and ResNet18 were all employed for classification	COVID-19 (Chest X-ray)

We have worked on two proposed models for detecting lung diseases using a chest radiography dataset as a prototype of our project.

5.1 Explanation of Analysis:

The research is carried out on a system with the following system configurations and software: Python 3 is used on Google Colab on a system consisting of Intel(R) Core(TM) i5-8400U CPU @4.0 GHz with 16 GB RAM and a 8GB GDDR5 Radeon RX 570 graphical processor unit. Besides, this research requires a massive dataset containing all types of medical images including X-ray, MRI, CT image with multiple classes Osteoporosis, Covid, Tuberculosis, Viral Pneumonia, Chest Cancer, Brain Tumor.

5.2 Requirements

We have tried to work with a sub part of our main dataset which consists of four classes including Covid,Tuberculosis, Pneumonia and Normal based on X_ray images where Covid, Tuberculosis, Pneumonia are containing images of patients and Normal is the class containing images of normal humans.

5.3 Description of Model

Firstly, our train set contains 2892 Covid images, 6012 Tuberculosis images, 1075 Pneumonia images and 8150 Normal images. We have splitted 15% of train data to make the validation set. Secondly, our test set contains 724 Covid images, 1202 Tuberculosis images, 270 Pneumonia images, 2042 Normal images.

5.3.1 Preprocessing

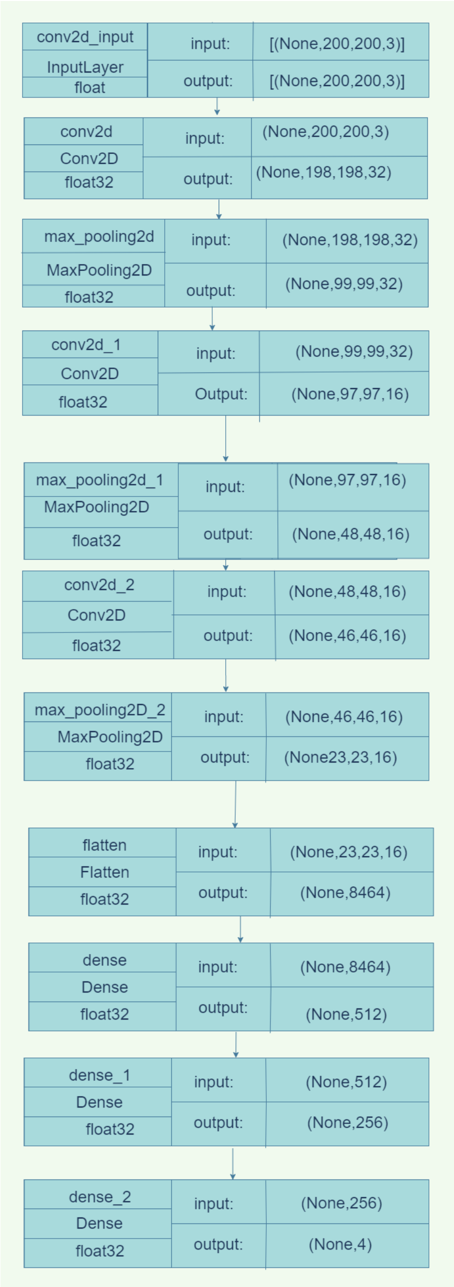
We imported image_dataset_from_directory from tensorflow.keras.utils to load the dataset as well as do some basic preprocessing steps . We labeled the dataset for four classes, defining the batch size of 32, resizing the image to height of 200 and width of 200 and splitting the data for the training set.

5.3.2 Model

The model we build is a basic Convolutional Neural Network using Sequential model. Firstly, we add three layers consisting of one Conv2D layer followed by one MaxPooling2D layer. In the first Conv2D layer, we used 32 filters, kernel size of (3, 3) and 'relu' activation function. In the second Conv2D layer, we used 16 filters, kernel size of (3, 3) and 'relu' activation function. In the third Conv2D layer, we used 16 filters, kernel size of (3, 3) and 'relu' activation function. Secondly, we add a Flatten layer to make the multidimensional input to a one dimensional flatten array to fetch in the Fully Connected layers(FC layers). Furthermore, we add three Fully Connected layers to classify the images to four classes. In the first FC layer, we added 512 neurons and used 'relu' activation. In the second FC layer, we added 256 neurons and again used 'relu'. In the last layer ,we added 4 units equal to the number of classes and used 'softmax' activation. Lastly, we used Adam optimizer and Binary Cross Entropy to compile our model. In our model there are 435,620 trainable parameters and 0 non-trainable parameters.

5.3.3 Design

The architecture of our proposed CNN model –



5.3.4 Challenges

We could not train our model on the main dataset due to the lack of resources. As a result , we trained the model on a sub dataset of our main dataset and gained satisfactory accuracy. Besides, the dataset we used is an imbalance dataset. In-order to balance this dataset we wanted to use different types of data balancing technique including data augmentation,smote . Due to the inefficient GPU that we have, we keep this step for further experiment when building the main model with the main dataset. Moreover, we tried to tune the hyperparameters including the number of Conv2d layers, MaxPooling2d layer, dense layers, filters , kernel size, strides, activation function, appropriate optimizer , learning rate of optimizer etc.

In hyperparameter tuning we also face the same problem of high standard GPUs . We could run up to three trials and the system crushed as well as the accuracy was not better than that we had previously. There are a lot of combinations in the hyperparameter tuning. As a result, we also had to avoid this process for now.

5.3.5 Preliminary Development of the Project

Our proposed CNN model has an accuracy of 97.73% on the training set , 81.39% on the validation set and 85% on the test set containing images of four different classes in the first trial of only 10 epochs. After doing some trial and test on the model, the test accuracy increases to 89.52% on 10 epochs . By balancing the dataset using data augmentation , smote the accuracy can increase more . Besides, hyperparameter tuning can be a good solution to find the best model which would give better accuracy. Moreover, we are thinking about using image enhancing techniques to get more satisfactory results.

Chapter 6

Conclusion

In this modern era of technology, loss of human lives due to misdiagnosis or unavailability of professionals cannot be accepted. If only in the United States an average of 60,000 people die each year by misdiagnosis, it must be alarming when we will count this number combining the whole population of this world. Therefore, our project aims to help the medical sector by advancing the diagnostic process through the delivery of a human-level analysis of a patient's medical condition. Our proposed model will just need a medical image (X-ray/MRI/CT scan) to detect the presence of any kind of abnormality inside the patient's body. Moreover, the system will be able to analyze the abnormality and show probable diseases or medical problems as output. This system will be able to help in early diagnosis of a disease, in emergency cases of a patient and in advancing the medical study to a greater level. Eventually, these will result in patients to get rid of misdiagnosis and to get the proper path of treatment at an early period of one's deteriorated medical conditions. As a result, plenty of lives will be saved from misdiagnosis all over the world.

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