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Classification of Brain MRI using CNN

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Abstract: The project is intended to classify the Brain MRI using the computer vision technique of Deep Learning. Brain MRI can be of two major types depending on the way they were extracted from the scanner as well as on the type of scanner and method used for taking the MRI of a subject. These two categories are T1weighted anatomical as well as T2weighted resting BOLD MRI images. These are categorized with the help of a Deep Neural Networks with 4 hidden layers. The dataset is taken from the openfmri. There are 120 MRI data and are released to the general public on as a part of the materials for “Temporal interpolation alters motion in fMRI scans: magnitude and consequence for artifacts detection” by Power et al. in PLOS ONE. Encased for each subject could be a T1-weighted anatomical picture (MP-RAGE) and one or extra T2*-weighted scans(resting bold outputs).The dataset we have is a 3D cuboid of the subject’s MRI image for the T1 weighted scans and 4D for the T2 weighted scans where the 1st, 2nd and 3rd being the x, y and z axis for the 3D image and the 4th dimension being the time. Every subject’s MRI is then split into 2D slices from all the axis to increase the data volume, then these images are pre-processed and fed into a 2D-CNN network. This is then trained for 3 epoch cycle in the cloud for a better processing speed and the resulted output of the weighted and biases are stored for the model to predict future inputs.

Keywords: MRI, BOLD, T1-weighted, T2-weighted, 2D-CNN.

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I. INTRODUCTION

MRI scan is associate degree investigation technique utilized in medical field that uses robust radio waves and magnetic field to provide pictures of structures and organs within the organic structure. This method has revolutionized the treatment of assorted ailments and finds ample applications in hospitals for staging of diseases, diagnosis etc. The data collected by MRI is formed into images. Those images correspond to some degree to what a black and white photo of the anatomy might look like if you cut the body apart and took a picture of it, but in fact the images give way more information than that.

T1 Weighted Image: T1 weighted picture (additionally alluded to as the "turn grid" unwinding time) is one among the fundamental attractive reverberation imaging beat groupings and shows varieties inside the T1 unwinding time of the tissues. A T1-Weighted picture relies on the longitudinal unwinding of a tissue's Net Magnetisation Vector (NMV). Basically, turns balanced in an external field (B0) accomplice degree place into the cross-section plane by a Radio-Frequency (RF) beat. They at that point slide back toward the main balance of B0. Not all tissues return to balance inside a similar amount of your time, and a tissue's T1 mirrors the quantity of time its protons' twists line up with the primary attractive field (B0)

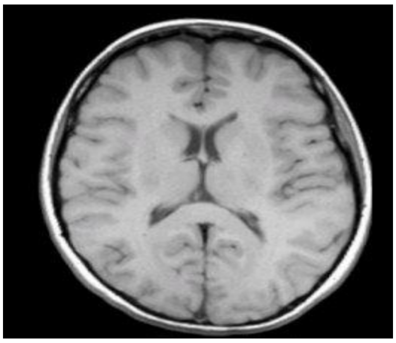

Figure 1: T1 Weighted Image

T2 Weighted Image: T2 Weighted Image (T2WI) is additionally one amongst the fundamental magnetic resonance imaging pulse sequence. The sequence weight shows variations within the T2 relaxation time of the tissues. The measure of T2 rot that a tissue encounters relies upon different elements. Each tissue has a characteristic T2 worth, anyway outer variables (for instance attractive field inhomogeneity) will curtail the T2 unwinding time. this additional outcome is unfree in T2*. The focalisation beat in turn reverberation successions helps to moderate these remote effects on the T2 unwinding time, making an endeavour to remain the picture T2 weighted as opposed to T2* weighted.

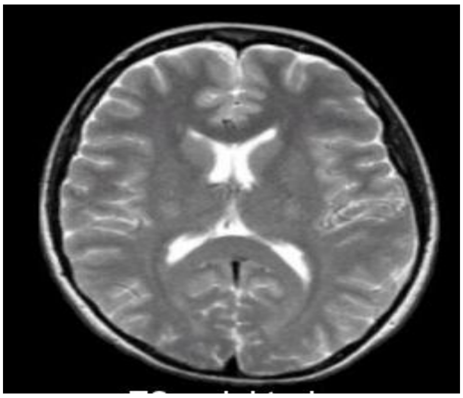

Figure 2: T2-BOLD Weighted Image

BOLD (Blood Oxygenation Level Dependent): Blood Oxygenation Level Dependent (BOLD) imaging is that the typical strategy used to create pictures in helpful MRI(FMRI) ponders, and relies upon provincial varieties in cerebral blood stream to outline territorial action. Blood stream inside the cerebrum is all around territorially controlled because of oxygen (O) and carbon dioxide (CO2) pressure of cortical tissue. When a chosen district of the cortex will build its movement in light of an undertaking, the extraction portion of oxygen from the local vessels winds up in an underlying drop in oxygenated hemoglobin (oxyHb) and an ascent in local carbon dioxide (CO2) and deoxygenated hemoglobin (deoxyHb). Following a slack of 2-6 cerebral blood stream (CBF) will increment, conveying an excess of oxygenated hemoglobin, washing ceaselessly deoxy-hemoglobin 1-2. it's this enormous bounce back in local tissue action that is imaged.

Machine learning: Machine learning is an innovation that licenses PCs to break down a given arrangement of data and gain from the bits of knowledge gathered from that dataset. By utilizing complex calculations a fake neural system is prepared that empowers our PCs to order, translate and comprehend information gave to it and after that utilization those bits of knowledge in tackling issues or foreseeing results. When an AI calculation is modified it improves and refreshes itself dependent on the information nourished to it.

Deep Learning: Deep Learning can be termed as a sub-branch or sub-set of Machine Learning that works on the basis of the structure and functions of a human brain. A human brain contains neural network that have interconnected neurons whose function is to process information and transmit signals among each other. Based on this idea, Geoffrey Hinton, the father of Deep Learning, built an Artificial Neural Network, that consisted of artificial neurons which are capable of performing different operations and processing information fed to it.

CNN (Convolution Neural Network): A neural network is an ensemble of processing nodes arranged in a layer-by-layer manner normally trained end-to-end in a supervised manner using gradient descent based algorithms such as stochastic gradient descent (SGD) algorithm. Neural networks learning is done in a hierarchical manner where each layer of the network learns more and more abstract features. The first layers learn atomic/primitive representations such as edges or color while the intermediate-level layers learn intermediate abstract representations such as object parts and finally high-level layers learn full objects like cats faces.

II. PROBLEM STATEMENT AND PROPOSED SOLUTION

Problem Statement: In Brain MRI research today, the scientists as well as researchers faces the problem of segregating the MRI into their types before actually working on the research. This takes a lot of time and manual effort. Suppose there are 1 million subjects, then separating the T1 weighted as well as Bold could take as long as a couple of months in the best case.

The process of segregation involves manually detecting that a MRI scan is Bold or T1 by processing the file using advanced cube marching algorithm. As well as there are a lot of chances of manual error while collecting them. The basic problems that have been faced while classifying the MRI images into T1 or BOLD is the human error. A doctor is a person who is involved with not only with one patient but they have to attend other patients as well. Not only other patients but also hospital management requires their assistance. With these multiple tasks that are already out there. It is very easy to make error while multitasking. And if even there is a minute error in the field of medical it can cause catastrophe. Even if there is a minute negligence in classifying MRI images especially when it comes to brain it can cause oversight of a certain tumour or a different fluid. For example in a T1 weighted image the csf fluid is observed as low signal intensity(black) while in a T2-BOLD image the csf fluid has high signal intensity(white), if the MRI image is mislabelled that will change the whole treatment process or the medical procedure that to be performed on the patient. There might a chance that patient will be operated without even having a disease will be operated because the mislabelled MRI will show the sign of disease or absence of that fluid.

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Mostly research paper that are available on detection of brain tumour usually take a classified data that is provided by the hospital and which is classified manually. This data can contain errors and these errors can further affect the results of the brain tumour detectors. This is because of the wrong data that was fed to neural network while training the data. Since the wrong data is fed to the neural network the outcomes cannot be totally reliable.
Usually available trained models that use neural network have the accuracy of 85%-93% and since it is a medical field the more the accuracy the better the result or reliability. These points were the basic motivation behind this project as the intent here is to decrease man power and give better and accurate results

Proposed Solution: We are using computer vision using deep neural network here. Each MRI scan will now be sent to our trained machine learning model which then can classify the type of MRI. We are using supervised learning algorithm on a 2D Convolutional Neural Network on a data that consist of 120 subjects. The classification of MRI images is a time-consuming process if it is done manually and which also has a risk of human error. In order to decrease the human error and manpower we made this project. The basic objective of the project is fast and accurate results which doesn't risk the life of any patient. The outputs of the project can be used for brain tumour detection as its output can be used as the input dataset for brain tumour detection model. The intent is to keep the accuracy at least 95% for better and accurate results.
Steps for making the model:

- Pre-processing the data
- Making a deep neural network and feeding the data to it
- Training the model
- Making a model.py file that would use the new inputs and predict the desired labe

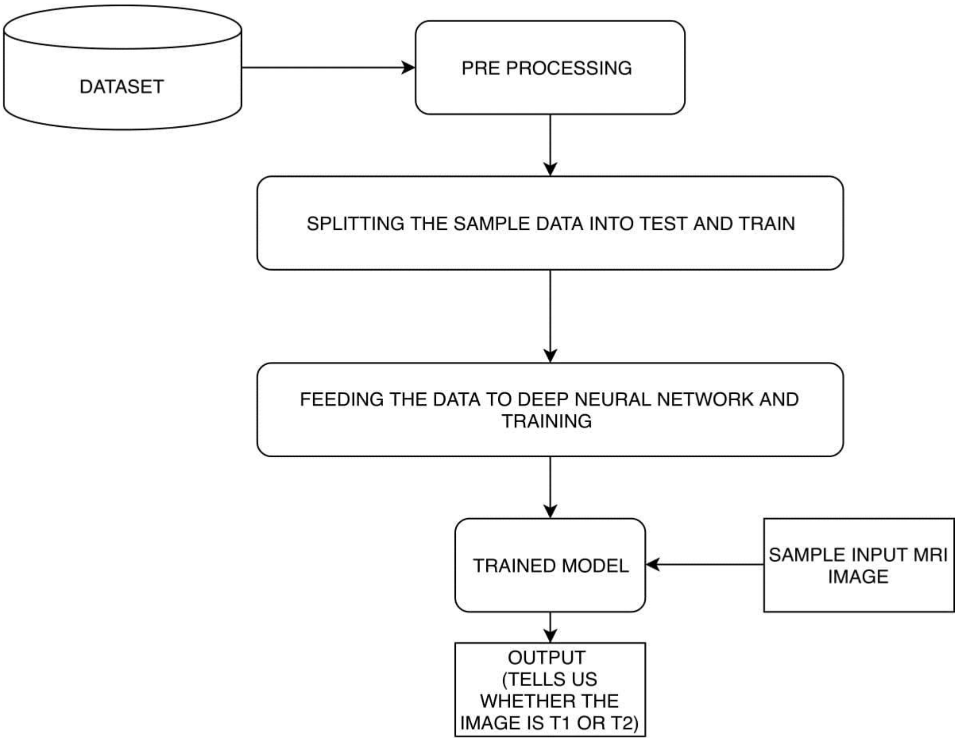

Figure 3: Flowchart of the project

Data Definition: This Project is intended to classify the brain MRI images as Bold or T1w pictures.This Dataset is Taken from openfmri https://openfmri.org/dataset/ds000243/These one hundred twenty mri datasets are being discharged to the general public on as a part of the materials for "Temporal interpolation alters motion in functional magnetic resonance imaging scans: magnitude & consequence for artifact detection" by Power et al. in PLOS ONE. Included for every subject is a T1-weighted anatomical image (MP-RAGE) & one or additional T2*-weighted scans (resting state bold scans)
All subjects

- were "typical" young adults that reportable no important medical specialty or psychiatric history
- were right-handed and reportable that English was their mother tongue
- were scanned at Washington University in Saint louis on a Siemens MAGNETOM Tim Trio 3T scanner with a Siemens 12-channel head coil
- were scanned using interleaved ascending product sequences for T2* information
- were scanned within the eyes-open resting state fixating a white crosshair on a black background

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The data are represented in multiple publications from the Petersen/Schlaggar cluster,

- starting with Power et al., 2013 “Evidence for hubs in human brain networks” in neuron
- and most comprehensively in Power et al., 2014 “Methods to sight, characterize, and take away motion object in resting state fMRI” in Neuroimage
- as well as many different publications
- Becky Coalson of the Petersen/Schlaggar cluster collated these scans and de-identified them for public unharness
- the accompanying file “WU120_subject_information.txt” contains for every subject
- the discharge subject range (1-120) - identical number utilized in this publication
- the subject number used in Power et al., 2014
- the owner/contributor of the data
- age of subject at scanning
- sex
- handedness
- English solely speaker
- paradigm of the resting state scans
- total scan time in resting state
- number of rest runs
- number of volumes per run
- TR of the runs
- scanner used (Siemens Tim Trio was in bay3)
- slice order (AFNI convention); sequences were ascending interleaved

PARTICIPANTS.TSV DOWNLOAD

participant_id	Age	Gender	Handedness	Native English Only	Total rest minutes
sub-001	24.74	F	R	yes	19.83
sub-002	23.32	F	R	yes	14.83
sub-003	24.33	M	R	yes	14.83
sub-004	25.14	M	R	yes	9.83
sub-005	25.1	F	R	yes	9.83
sub-006	24.63	F	R	yes	9.83
sub-007	28.64	M	R	yes	9.83
sub-008	24.41	F	R	yes	9.83
sub-009	26.27	M	R	yes	30.0
sub-010	31.73	F	R	yes	30.0
sub-011	24.41	M	R	yes	30.0
sub-012	26.2	F	R	yes	30.0

Figure 4: Data of first 12 Subjects

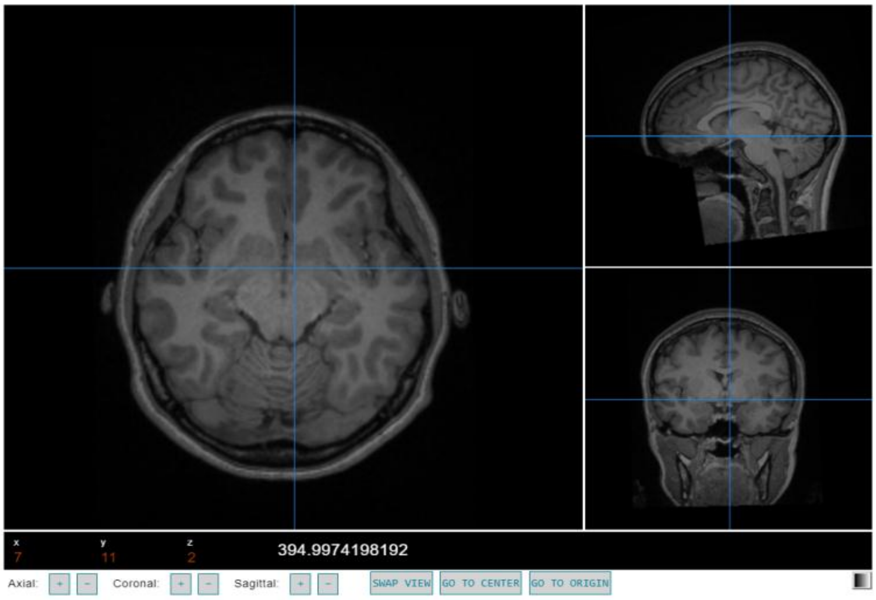

Figure 5: T1w MRI scan of sub001

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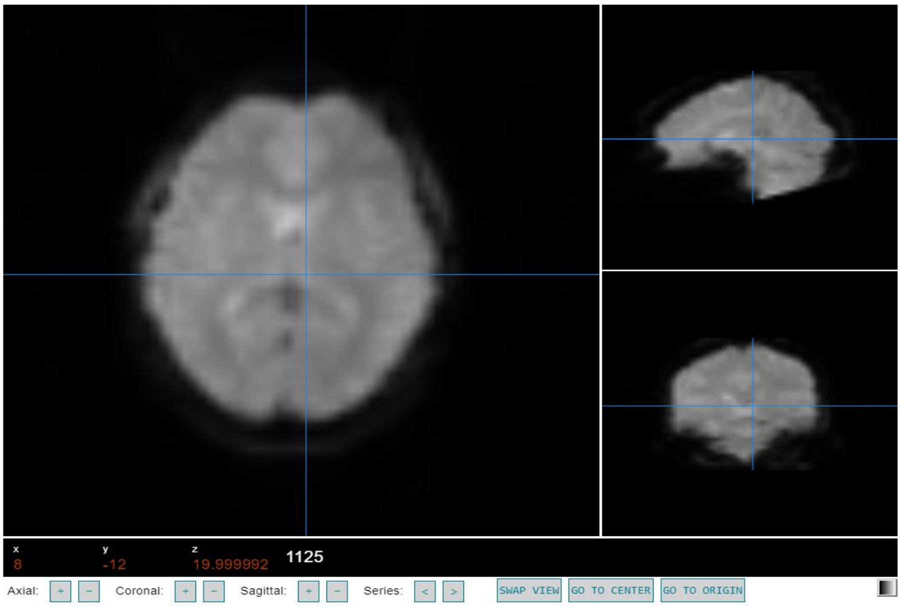

Figure 6: T2-BOLD MRI scan of sub001

Software Specifications:

1. Operating System: WIN XP or higher
2. Software Required: Anaconda Navigator
3. Jupyter Notebook
4. Pychar

Hardware Specifications:

1. Procession: Pentium IV or above
2. Ram: 2 GB or more
3. Space Requirements: More than 100 MB

Python Libraries used:

1. OS
2. MATH
3. CV2
4. TFLEARN
5. MATPLOTLIB
6. NUMPY
7. NIBABEL

Pre-processing of Data: Here is the algorithm of the preprocessing module

1. Start
2. Input the data and store it in list named “dataset”
3. Create 2 variables “IMG_PX_SIZE = 80” “HM_SLICES = 16”
4. Until dataset ends
    4.1 call process module
        4.1.1 if not bold
                label [0,1] and convert 3d to 2d
            else
                label [1,0] and convert 4d to 2d
        4.1.2 call chunk module
                creates total chunks of 16 in number
        4.1.3 call module mean
                find the mean of each chunk
        4.1.4 returns the label and mean list
5. Create a single list of mean and label
6. Save it in a file

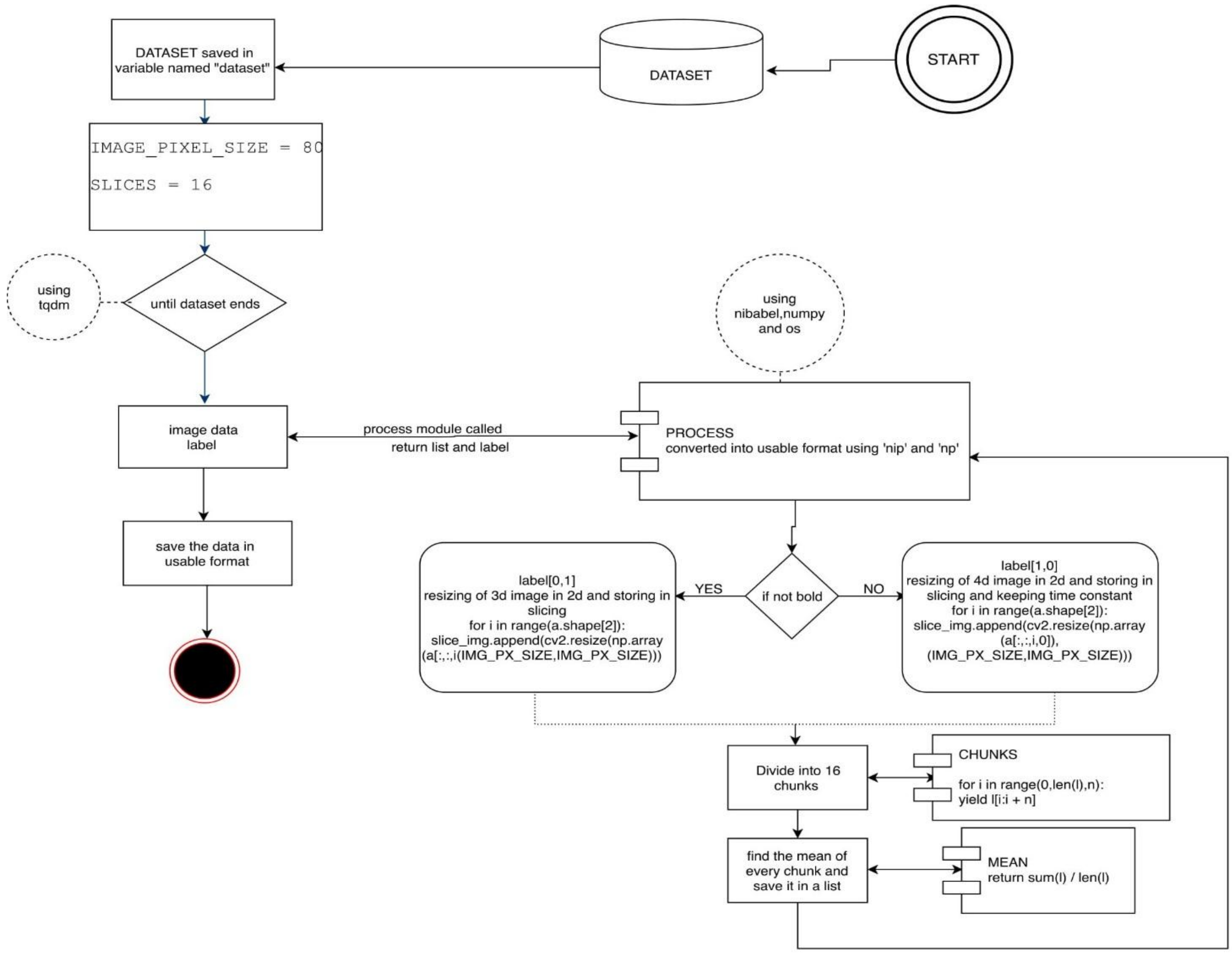

Figure 7: Data Flow Diagram of pre-processing stage

III. RESULT ANALYSIS AND CONCLUSION

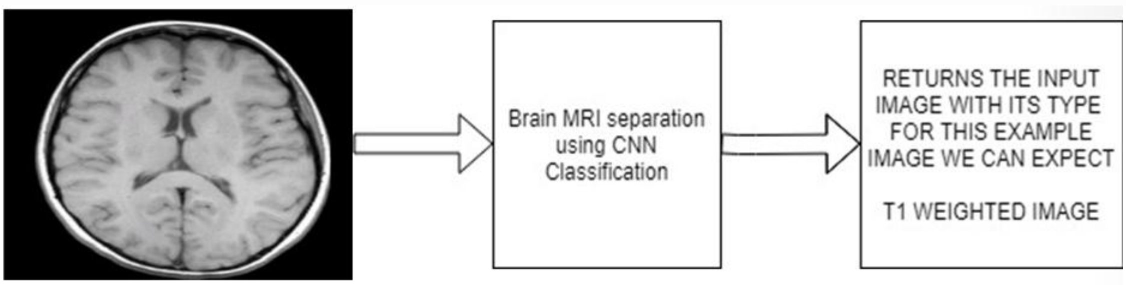

Figure 8: Working of the Model

We will be predicting whether the images provided as input are either T1 or T2 bold within very short span of time with a greater deal of accuracy and precision which is not possible when handled manually because even the experts are sometimes liable to commit a mistake. Here we are removing the chances of human error. As we can see in figure 11 the model will take the MRI image of the brain taken from MRI machine then the scan will be fed to the model and the model will the user whether the provided image or MRI scan is T1 weighted or T2-bold. The accuracy that we have achieved in this model is 99.46%.

This is accuracy graph of the model. This graph is plotted between accuracy and time. Time is taken on y axis while accuracy is taken on x axis. As we can clearly see from the graph that the accuracy of the model increases with time until 60.00. there is a dip in the accuracy but it increases again after that dip and ultimately reaches 99.46% at the end of the program. This shows that the model is very accurate. Two small dips can be seen in this graph but the graph ends at high note leaving accuracy more than 95%.

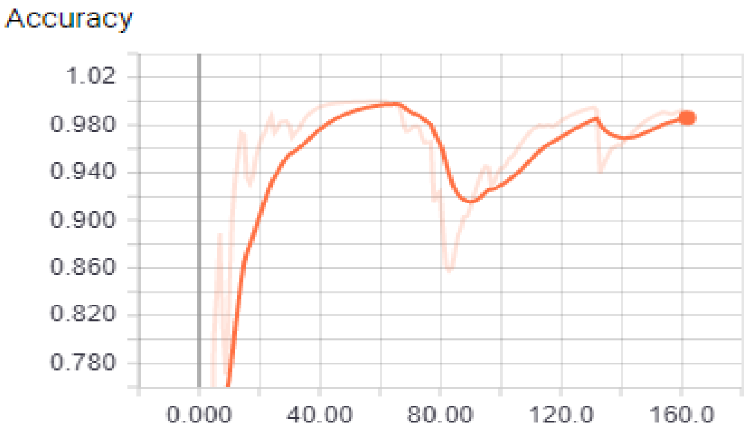

Figure 9: Accuracy Graph

VI. CONCLUSION

The motivation of this study developed from a desire to learn, understand, and apply concepts of deep learning and convolution neural network. *Brain MRI separation using CNN classification*, served as a framework for introductory convolution neural network methods. The goal in this project was to build a model to separate or classify the MRI scanned images into T1 Weighted and T2 BOLD scans. The dataset was downloaded from openfmri website where this dataset containing MRI scans of 128 subjects was made available to general public by SEIMENS HEALTHCARE. A significant amount of time and effort was spent in pre-processing, training, and refining the model

We hypothesize that this phenomenon could be attributed to the structure of the data. That is, we believe there is more to the data than what we have discovered and the data may require additional restructuring to obtain further improvement when using the methods that have been covered.

We look forward to make or updates this project with time as it has multiple and a vast future scope making it more flexible and reliable source of obtaining labelled MRI scans. This project will help medical field in a very unique kind of way as it has a potential and scope of improvement. We used 2d convolution neural network instead of 3d convolution neural network as it has more processing speed and we are making the project more and more efficient

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BIOGRAPHY

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