A PRELIMINARY REPORT ON

Brain Tumor Classification Using Deep Learning Algorithms

SUBMITTED TO THE SAVITRIBAI PHULE PUNE UNIVERSITY, PUNE IN THE PARTIAL FULFILLMENT OF THE REQUIREMENTS FOR THE AWARD OF THE DEGREE

OF

BACHELOR OF ENGINEERING
(COMPUTER ENGINEERING)

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CERTIFICATE

This is to certify that the following students of Final Year Computer Engineering of PES's, Modern College of Engineering have successfully completed the preliminary analysis and design of project entitled **"Brain Tumor Classification Using Deep Learning Algorithms."** under the guidance of Mr. Santosh Nagargoje.

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This is in partial fulfillment of the award of the degree Bachelor of Computer Engineering of Savitribai Phule Pune University.

Date:

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Acknowledgement

It gives us pleasure in presenting the partial project report on **'Brain Tumor Classification Using Deep Learning Algorithms '**.

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Abstract

Brain tumor is considered as one of the aggressive disease, among children and adults.Brain tumors account for 85 to 90 percent of all primary Central Nervous System(CNS) tumors. Every year, around 11,700 people are diagnosed with brain tumor. The 5-year survival rate for people with a cancerous brain or CNS tumor is approximately 34 percent for men and 36 percent for women. Brain Tumors are classified as: **Benign Tumor, Malignant Tumor, Pituitary Tumor, etc.** Proper treatment planning and accurate diagnostics should be implemented to improve life expectancy of the patients.

The best technique to detect brain tumor is **Magnetic Resonance Imaging (MRI)**. Huge amount of data images are generated through the scans. These images are examined by the radiologist. Manual examination can be error prone due to the level of complexities involved in brain tumors and their properties.

Application of automated classification techniques using **Machine Learning(ML) and Artificial Intelligence(AI)** has consistently shown higher accuracy than manual classification. Hence, we propose performing detection and classification by using Deep Learning Algorithms using Convolution Neural Network (CNN)[1] and Artificial Neural Network (ANN)[2] to achieve higher accuracy.

The MRI images are classified using different **'Deep Learning Models of ANN and CNN'**. These models have permutations and combinations of different 'Network Parameters'. The model with the highest accuracy is selected and deployed.

The aim of the project is to achieve higher accuracy and reliability for real world MRI data using AI and ML domain knowledge. Further to accurately indicate any growth or shrinkage in tumor and to provide some suggestions for treatment by providing ease of access of the software through cloud and mobile applications, web browsers platforms.

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List of Abbreviations

AI .... Artificial Intelligence

ANN .... Artificial Neural Network

AWS .... Amazon Web Services

CNN .... Convolution Neural Network

CNS .... Central Nervous System

DNN .... Deep Neural Network

EC2 .... Amazon Elastic Compute Cloud

ML .... Machine Learning

MRI .... Magnetic Resonance Imaging

NN .... Neural Network

SQL .... Structured Query Language

1.

Introduction

1.1 Motivation

Brain Tumors are complex. There are a lot of variations in sizes and location of tumor. This makes it really hard for complete understanding of tumor. Also a professional Neurosurgeon is required for MRI analysis. Often times in developing countries the lack of skillful doctors and lack of knowledge about tumors makes it really challenging and time-consuming to generate reports from MRI's. So an automated system on Cloud[11] can solve this problem. The automated system would be able to decide is the MRI has a tumor and the system would be able to pin-point the exact type of tumor identified.[3] The system would also be able to maintain records of patients and track tumor size. Providing list of doctors, suggestions and further medical diagnostic procedure would help eliminate any confusion among patients.

1.2 Problem Definition

To Detect and Classify Brain Tumor using CNN and ANN as an asset of Deep Learning and to examine the change of the tumor size.

1.3 Computation complexity

- **P Problem :**
  In our project if the input MRI provided by the user is valid and our system strikes all confidence in the first iteration then our problem is completed in polynomial time and hence it is a 'P Problem'.
- **NP Problem :**
  If our system does not receive a valid MRI or if our system is not completely confident about the class of tumor in first iteration it reruns the iteration with some modifications, in such case the problem does not run in polynomial time so it becomes a 'NP Problem'.

2.

Literature Survey

2.1 Literature Survey

Number	Research Papers/Journal	Authors	Publications	Comments /Analysis /Problems
1	Multi Classification Of Brain Tumor Images	Hossam H. Sultan, Nancy M. Salem, Walid Al-Atabany	IEEE 2019	CNN Based Classification With Augmentation
2	Brain Tumor Classification Using Convolutional Neural Networks	J.Seetha, S.Selvakumar Raja	Biomedical Pharmacology Journal, September 2018.	CNN Based Classification
3	Deep Learning based brain tumor classification and detection system	Ali Ari, Davut Hanbay	Turkish Journal of Electrical Engineering and Computer Sciences 2018	ELR-LRM Based Classification
4	A Review on Image Processing and Image Segmentation.	Jiss Kuruvilla,Dhanya Sukumaran,Anjali Sankar,Siji P Joy	IEEE,2016	Overview of Image Processing and Image Segmentation
5	Brain Tumor Segmentation Using Deep Learning by Type Specific Sorting of Images	Zahra Sobhaninia, Safiyeh Rezaei, Alireza Noroozi, Mehdi Ahmadi, Hamidreza Zarrabi, Nader Karimi, Ali Emami,	Research Gate 2019	Sorting Of Images 1. Sagittal View 2.Axial View 3.Coronal View

Table 2.1: Literature Survey

3.

Software Requirements Specification

3.1 Introduction

3.1.1 Project Scope

1. Create models using ANN and CNN algorithms.
2. Selecting best model with tuned hyper-parameters for MRI classification.
3. Maintain patient records.
4. Display of growth or shrinkage of Tumor.
5. Reduction in Medical negligence or Human error.

3.1.2 User Classes and Characteristics

1. **Doctor :**
    (a) To identify if Tumor is present or not.
    (b) For validation of tumor class.
    (c) To monitor Tumor growth or shrinkage.
    (d) To analyze the MRI Reports of the patients.
2. **Patient :**
    (a) To keep account of MRI reports.
    (b) To check on available hospitals, doctors, medicines.

3.1.3 Assumptions and Dependencies

1. **Assumptions :**
    (a) Proper MRI images.
    (b) Updated Web Browser.
    (c) Android Phone (Kit-kat (4.4) or higher).
    (d) iPhone (iOS (10) or higher).
2. **Dependencies :**
    (a) Cuda Toolkit .
    (b) TensorFlow.
    (c) Keras.
    (d) Flask.

3.2 Functional Requirements

1. **Open Architecture :**
   There is no standard or uniform infrastructure platform. The key consideration is whether the analytic solution works with multiple platforms.

2. **Alert Generation :**
   When a machine degradation or potential asset failure is detected, this is communicated to the relevant facility stakeholders.

3. **Human Error Correction :**
   The system confirming if the input from user is valid. An invalid input will generate invalid results.

3.3 External Interface Requirements

3.3.1 User Interfaces

1. **Front-end Software :** Mobile Operating System (Android/IOS), Web Browser.

2. **Back-end Software :** Anaconda Navigator (v5.3.0), Colaboratory Interface.

3.3.2 Hardware Interfaces

1. Windows based Computer.

2. Amazon EC2.

3. Android and iOS smartphones.

3.3.3 Software Interfaces

1. **Operating system :**
   We have chosen Windows operating system for its best support and user-friendliness.

2. **Database :**
   We use SQL to store user login details.

3. **File System :**
   We use file system to store MR images.

4. **BootStrap :**
   It contains CSS and JavaScript based design templates for typography, forms, buttons, navigation and other interface components and JavaScript-based design templates for typography, forms, buttons, navigation and other interface components.

3.3.4 Communication Interfaces

1. Mobile Application (Android and iPhone).

2. Web Browsers.

3. Wifi.

4. Ethernet.

3.4 Non-functional Requirements

3.4.1 Performance Requirements

1. **Workload :**
   The software system consists of large amount of data-sets of MR images (.jpeg format).

2. **Scalability :**
   The software system should be able to process data above the systems workload.

3. **Platform :**
   The software system should be compatible with multiple mobile Operating Systems (Android,iOS).

4. **Reliability :**
   The system should be reliable and should provide accurate results. The information of estimate cost and list of doctors should be appropriate.

3.4.2 Safety Requirements

1. Data-set Verification.

2. Bug-free Mobile Applications.

3.4.3 Security Requirements

1. Authorized AWS Login.

2. HTTPS enabled servers.

3.4.4 Software Quality Attributes

1. **Accuracy :**
   The software must accurately identify the tumor present in MRI and segregate the tumor into different types.

2. **Portability :**
   The software system should be available on different smart phones (Android and iPhones).

3. **Robustness :**
   Robustness reduces the impact of operational mistakes, erroneous input data and hardware errors.

3.5 System Requirements

3.5.1 Cloud Server Requirements

1. **AWS :**
   (a) INSTANCE : p2.8xlarge
   (b) GPU : 8 X NVIDIA K80
   (c) CPU : INTEL 32 vCPUs
   (d) GPU MEMORY : 96 GB
   (e) MEMORY : 488 GB
   (f) COST : 7.200 USD/hr
2. **Paper Space :**
   (a) GPU : 1 X NVIDIA P6000
   (b) CPU : INTEL 8 vCPUs
   (c) GPU MEMORY : 16 GB
   (d) MEMORY : 30GB
   (e) COST : 0.51 USD/hr

3.5.2 Software Requirements

1. Anaconda Navigator (v5.3.0)
2. Jupyter Notebook (v6.0.1)
3. Python (v3.7)
4. Google Colab
5. Android Studio (v3.5)
6. Swift Studio (v4.1)
7. Cuda Toolkit (v10)
8. Flask Framework (v1.1.1)

3.5.3 Hardware Requirements

1. Graphic Card : Nvidia's Titan V(12 GB RAM(GDDR6)), Tesla K80(12 GB RAM)
2. CPU : Intel
3. RAM : 16 GB (DDR4)
4. Other: Network Card.
5. iPhone / Android phone

3.6 Analysis Models: SDLC Model (Incremental Model)

We have used the following model of Software Development Life Cycle .

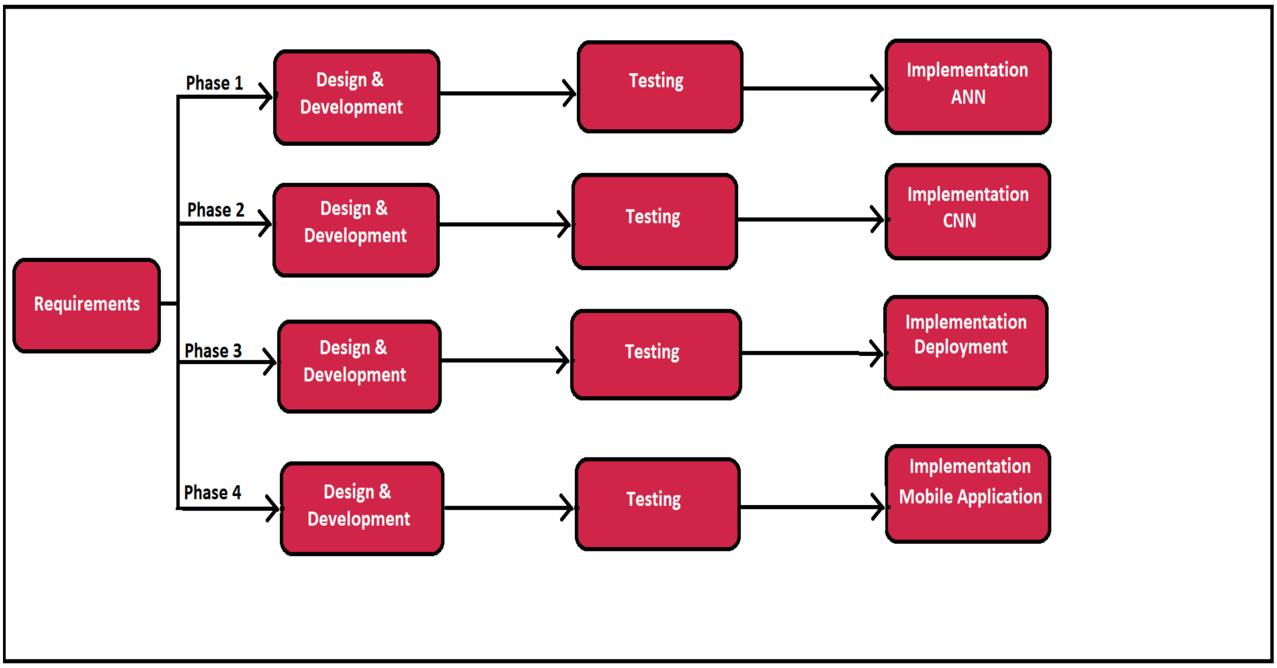

Figure 3.1: Incremental Model

Incremental Model :
Incremental Model is a process of software development where requirements divided into multiple standalone modules of the software development cycle. In this model, each module goes through the requirements, design, implementation and testing phases. Every subsequent release of the module adds function to the previous release. The process continues until the complete system achieved.

The modules implemented are:

Module 1 : ANN Model Building.
Module 2 : CNN Model Building.
Module 3 : Deployment (Cloud Platform).
Module 4 : Mobile Application Development.

The System is built after the implementation of all the 4 Modules.

3.7 System Implementation Plan

Project Title	Group Id	Start Date	End Date
Brain Tumor Classification Using Deep Learning Algorithms	02	8th August 2019	8th March 2020

Table 3.1: System Implementation Plan

1. **Implement -**

A. **Pre-Processing**

Number	Function	Description
1	Edge Detection	Using Edge detection algorithms to identify tumor.
2	Augmentation[18]	Using Python Data Generator to augment data images.

Table 3.2: Pre-Processing

B. **Model Design**

Number	Function	Description
1	ANN	Building models using Artificial Neural Network.
2	CNN	Building models using Convolution Neural Network.
3	Hyper-Parameters	Fine tuning the hyper parameters of the model.

Table 3.3: Model Design

2. **Testing -**

Number	**Function**	**Description**
1	F1 Score	Test models to obtain acceptable F1 score.
2	Cross Validation	Test models to obtain high accuracy values on unseen datasets.
3	Selenium tool	Using selenium for web page testing.

Table 3.4: Testing

3. **Deployment -**

Number	**Function**	**Description**
1	AWS	Amazon EC2 to deploy model on cloud.
2	Paper Space	Using Paper Space to train and test models.

Table 3.5: Deployment

4. **Project Status Report -**

Activity Number	**Project Activity**	**Submission Date**	**Status**
1	Project Group Registration and Domain Registration	21st June 2019	Complete
2	Domain research	23th August 2019	Complete
3	Guide Allocation and Title Finalization	24th August 2019	Complete
4	Project Review	29th August 2019	Complete
5	Project Synopsis Submission	16th September 2019	Complete
5	Data Certification	29th September 2019	Complete
7	Industrial Review	5th October 2019	Complete
8	I2I Project Competition Registration	9th October 2019	Complete
9	Preliminary Report Submission	-	Incomplete
10	Project Implementation	-	Incomplete
11	Mobile application Design and Implementation	-	Incomplete
12	Project Testing	-	Incomplete
13	Deployment	-	Incomplete
14	Research paper publication	-	Incomplete

Table 3.6: Project Status Report

4.

System Design

4.1 System Architecture

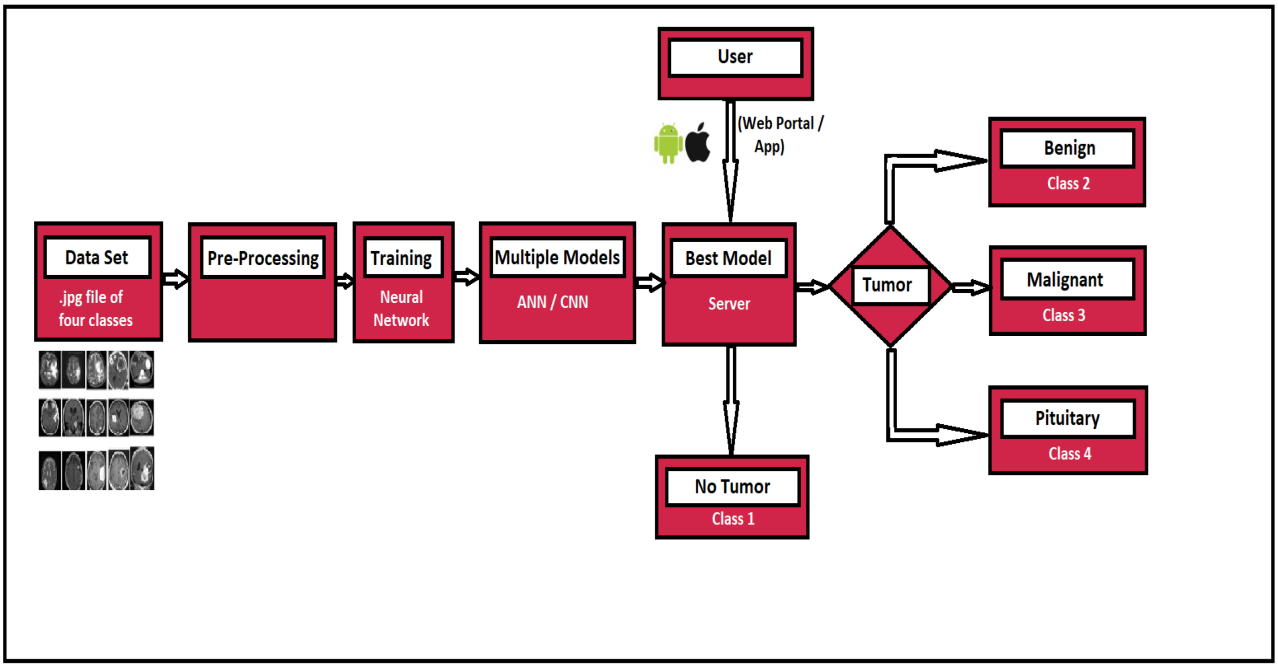

Figure 4.1: Architecture Diagram (Fig.1)

- **Data-set Block :**
  This block represents data collection process. Image data is gathered and validated in this process block.[6]

- **Pre-Processing Block :**
  The validated data is cleaned and augmented. Various data pre processing algorithms like edge detection, padding are applied on data.[4]

- **Training :**
  Various ANN and CNN models are trained on pre processed data. The models are monitored for accuracy and many other parameters.

- **Multiple Models :**
  Training generates multiple models. The best model is selected based on multiple parameters. Alex Net.[15], Res Net.[16], Image Net.[17] , custom model net are all tested. The best model has highest accuracy value and lowest loss value, etc.

- **Best model :**
  The best model[8] is hosted on the cloud along with other python script. The model accepts image as input from user and generates output as class titles.

- **User :**
  The user connects to the model using web service or mobile applications. The user sends his/her MRI to the model and expects a class label as answer.

- **No Tumor :**
  If user receives Class 1 as output, it means there is no tumor is detected in the MRI.

- **Benign :**
  If user receives Class 2 as output, it means Benign Tumor is detected in the MRI.

- **Malignant :**
  If user receives Class 3 as output, it means Malignant Tumor is detected in the MRI.

- **Pituitary :**
  If user receives Class 4 as output, it means Pituitary Tumor is detected in the MRI.

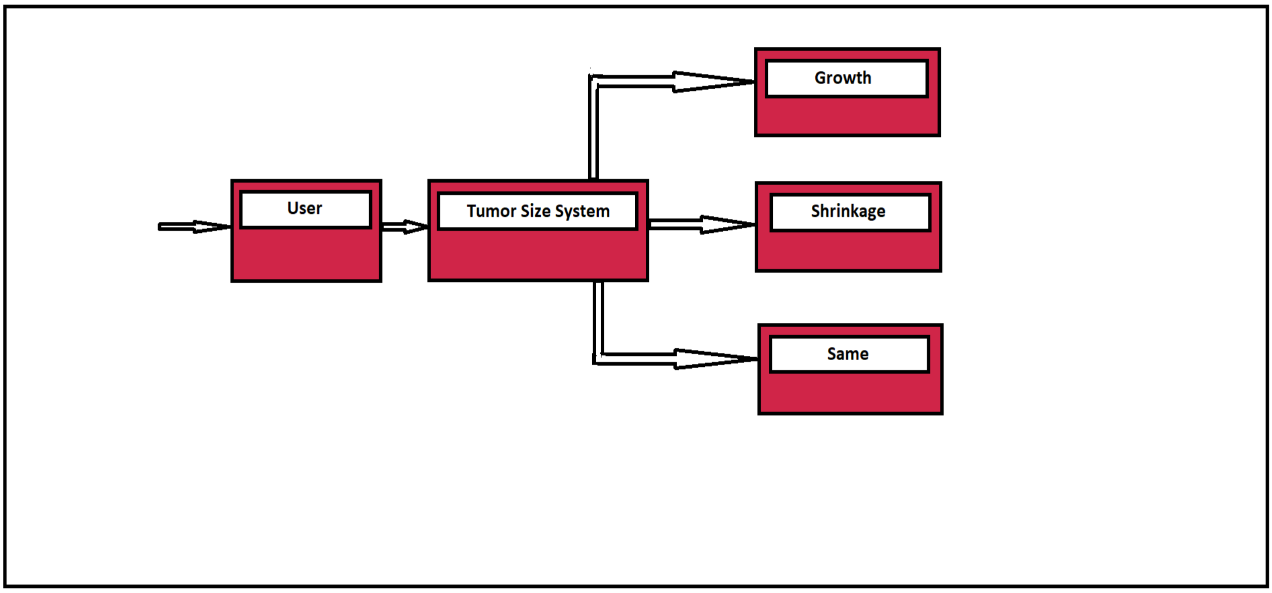

Figure 4.2: Architecture Diagram (Fig.2)

- **User :**
  The user inputs a new MRI to the system and expects answer if there is change in tumor size or not.

- **Tumor Size System :**
  This system receives the new MRI and compares it with old MRI to check for changes in tumor size.

- **Growth :**
  This class label is generated when tumor new MRI has a tumor size greater than the old MRI.

- **Shrinkage :**
  This class label is generated when tumor new MRI has a tumor size smaller than the old MRI.

- **Same :**
  This class label is generated when tumor new MRI has a tumor size same as the old MRI.

4.2 Model Architecture

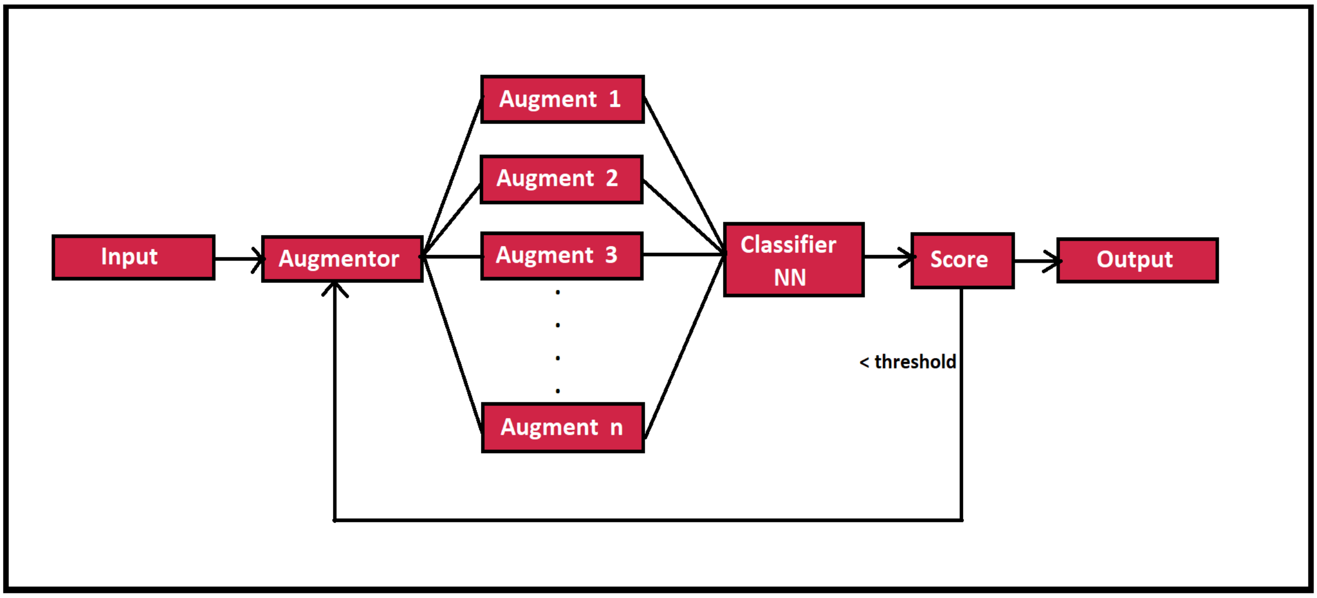

Figure 4.3: Architecture Diagram (Fig.3)

- The model receives input an MRI as input. The model then augments this image into 'n' different images through the process of **Data Augmentation**[18]. The 'n' different images are fed to the Neural Network for classification.
- The neural network classifies 'n' images into four classes. Then we take votes from each class. If vote of a particular class is greater than threshold vote confidence, we declare that class label as the output which is sent to back to the user.
- If the threshold is not met, the Image Augmentator is called which generated new 'n' images and they are again sent to NN. This process is executed until, the threshold vote confidence is met or no of tries('t') is reached.
- Thus by taking votes, we reduce the probability of error. This makes the system more robust.

4.3 Data Flow Diagrams

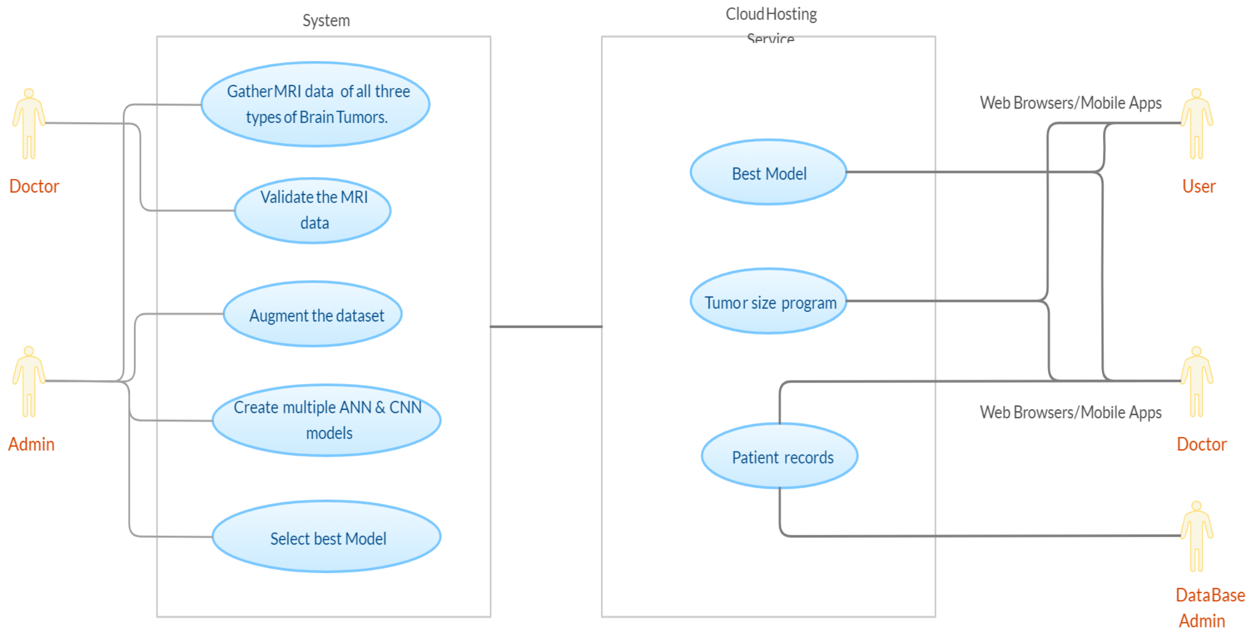

Figure 4.4: Data Flow Diagram

DFD Level: Zero (0) Level.

- **Administrator :**
The administrator is responsible to collect valid image data from online sources as well as request data from hospitals.The group augments the data and creates various ML models and selects the best model.

- **Doctor :**
The doctor in the system design phase is responsible to validate the MRI data gathered by the group and provides data validation certificate to the group.

- **User :**
The user is a patient who uses Web or mobile applications to connect to the model which is hosted on cloud. The user may also request report about change of tumor size.

- **Doctor :**
The doctor connecting to cloud services represent a handler of patients. Accordingly the doctor can act as an user or can access records of valid patients.

- **Database Administrator :**
The database administration is responsible to manage the database at the back end.

4.3.1 Data Flow Stages

1. **Pre-Processing Stage :** Pre processing of Image data helps clean the data to be fed as input into NN models. Models with clean and accurate data yield high F1 scores.
   (a) Normalization.
   (b) Edge Detection (Canny/Sobel).
   (c) Data Augmentation.
   (d) ZCA Whitening.
2. **Model Building Stage :** Model Building stage[5] is where we create multiple models using permutations and combinations of various hyper parameters. We also look at accuracy graphs over epochs.
   (a) Max Pooling.
   (b) ANN Model .
   (c) CNN Model.
   (d) Convolution.
   (e) Activation Functions.
3. **Deployment Stage :** The best model is deployed on Cloud Platform[9] along with its weights and other support for access, login support and database connectivity.
   (a) AWS Cloud.[10]
   (b) Paper Space.
   (c) Flask.
   (d) Docker.
4. **Mobile Application Stage :** For ease of access user can download mobile applications which would be supported by the Cloud Provider.[14]
   (a) Android Platform (.apk file). [12]
   (b) iPhone Platform (.ipa file).[13]

5.

Other Specification

5.1 Advantages

1. The Deep Learning model selected among multiple models gives high F1 score, highest accuracy percentage and lowest error rate.
2. The model runs on Cloud Services and can be accessed anywhere.
3. The system can acknowledge growth or shrinkage of tumor.
4. The system maintains records of multiple patients.
5. Intern doctors are able to understand MRI and make proper suggestions.

5.2 Limitations

1. The system does not flag invalid image inputs.
2. The system cannot predict any other type of tumor.
3. The model runs on Cloud Services and needs internet access.

5.3 Applications

1. Patients with MRI can immediately check their report through the mobile applications.
2. Doctors with in-confident knowledge about tumor can guide the patient through validation using the system.
3. Patients and Doctors can track changes in tumor size.
4. Patients can view alternative hospitals and doctors which would provide treatment.
5. Users no longer have to wait for results of MRI reports.

6.

Conclusion

1. We have created multiple Deep Learning Models using Artificial Neural Network as well as Convolution Neural Network.
2. We select the best of Convolution Neural Network or Artificial Neural Network model with highest accuracy and lowest error rate for deployment on Cloud Platform.
3. The system can be accessed by users and doctors through Web-Browsers or Android or iOS applications.
4. The system is able to correctly classify Brain Tumors and also examine about changes in tumor size.
5. The best possible NN architecture for the automation of classification of brain tumor MR images into 4 classes :No Tumor, Benign Tumor, Malignant Tumor and Pituitary Tumor is studied.

7.

Appendix - A

- **Technical Feasibility**

  The project will be implemented using programming languages like python and web development tools. Server services like AWS[10] would be used to implement the model on a website to access it from anywhere. The project will be implemented to analyze the MRI and detect the presence or absence of a brain tumor. If present, the project classifies the tumor between 3 labels.[7]

- **Computational Feasibility**

  Computational complexity theory focuses on classifying computational problems according to time taken to solve them. A computation problem by a system using an algorithm to solve the given problem with the help of valid and complete data needed.

- **Economic Feasibility**

  This project requires AWS services[9] fee for computing a given MRI and implementing the model.

- **Operational Feasibility**

  The algorithm implemented can be improved to increase accuracy by tweaking the model variables and training it with a larger dataset. The system will efficiently detect brain tumor and its type from a give MRI.

8.

Appendix - B

- **J. Seetha and S.Selvakumar Raja, "Brain Tumor Classification Using Convolutional Neural Networks", 2018.**

  The brain tumors, are the most common and aggressive disease, leading to a very short life expectancy in their highest grade. MRI images are used to diagnose tumor in the brain. However the huge amount of data generated by MRI scan thwarts manual classification of tumor vs non-tumor in a particular time. In this work, automatic brain tumor detection is proposed by using Convolutional Neural Networks (CNN) classification. The deeper architecture design is performed by using small kernels. Experimental results show that the CNN archives rate of 97.5% accuracy with low complexity and compared with the all other state of arts methods.

- **ALI ARI and Davyut Hanbay, "Deep learning based brain tumor classification and detection system", 2018**

  The brain cancer treatment process depends on the physician's experience and knowledge and thus, using an automated tumor detection system is extremely important to aid radiologists and physicians to detect brain tumors. The purpose of the study was using only cranial MR images, which have a mass, in order to save the physician's time. In the experimental studies the classification accuracy of cranial MR images is 97.18%. Evaluated results showed that the proposed method's performance was better than the other recent studies in the literature. Experimental results also proved that the proposed method is effective and can be used in computer aided brain tumor detection.

- **Mohammad Havaei , Axel Davy , David Warde, Antoine Biard, Aaron Courville ,Yoshua Bengio ,Chris Pal ,Pierre-Marc Jodoin, Hugo, "Brain Tumor Segmentation with Deep Neural Networks", 2015**

  In this paper, we present a fully automatic brain tumor segmentation method based on Deep Neural Networks (DNNs). The proposed networks are tailored to glioblastomas (both low and high grade) pictured in MR images. We present a novel CNN architecture which differs from those traditionally used in computer vision. Our CNN exploits both local features as well as more global contextual features simultaneously. Also, different from most traditional uses of CNNs, our networks use a final layer that is a convolution implementation of a fully connected layer which allows a 40 fold speed up. We also describe a 2-phase training procedure that allows us to tackle difficulties related to the imbalance of tumor labels.

- **Hossam H. Sultan, Nancy M. Salem, Walid Al-Atabany, "Multi-Classification of Brain Tumor Images Using Deep Neural Network", 2019**

  Brain tumor classification is a crucial task to evaluate the tumors and make a treatment decision according to their classes. Deep learning (DL) is a subfield of machine learning and recently showed a remarkable performance, especially in classification and segmentation problems. In this paper, a DL model based on a convolutional neural network is proposed to classify different brain tumor types using two publicly available datasets. The former one classifies tumors into (meningioma, glioma, and pituitary tumor). The other one differentiates between the three glioma grades (Grade II, Grade III, and Grade IV). The proposed network structure achieves a significant performance with the best overall accuracy of 96.13% and 98.7%, respectively, for the two studies.

- **Jiss Kuruvilla, Dhanya Sukumaran, Anjali Sankar, Siji P Joy, "A Review on Image Processing and Image Segmentation"**

  A methodological study on significance of image processing and its applications in the field of computer vision is carried out here. During an image processing operation the input given is an image and its output is an enhanced high quality image as per the techniques used. Our study provides a solid introduction to image processing along with segmentation techniques, computer vision fundamentals and its applied applications. The segmentation method can be divided into different type based on the constraint selected for segmentation like pixel intensity, homogeneity, discontinuity, cluster data, topology etc. A single approach to segment all variety of images may be practically unfeasible.

9.

Appendix - C

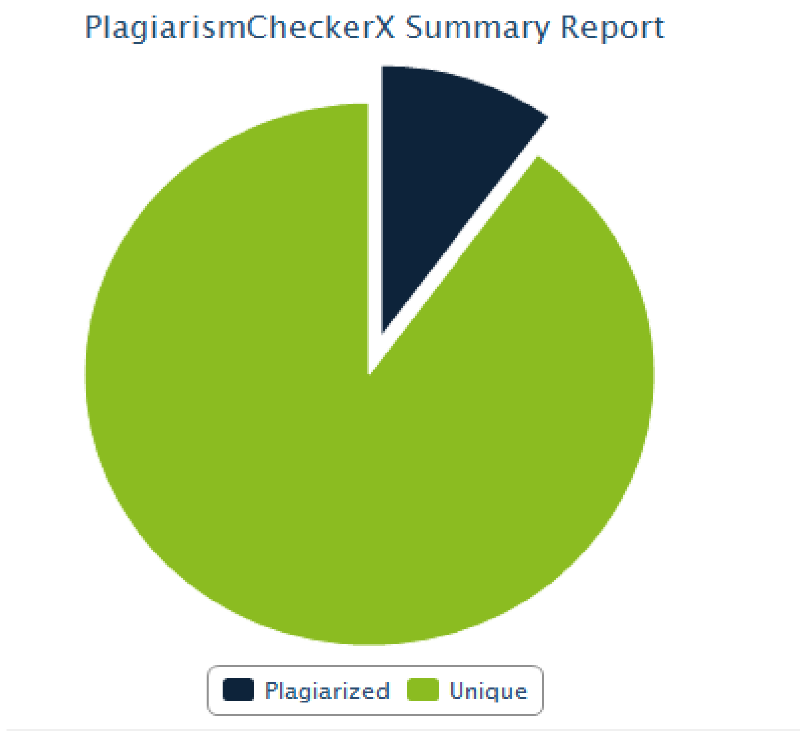

Figure 9.1: Plagiarism Diagram

1. Software : PlagiarismCheckerX
2. Uniqueness : 90 percent
3. Plagiarized : 10 percent

10.

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Data Sets:

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https://github.com/Swati707/brain-tumor-classification/tree/master/Datasets

- Kaggle : Brain Tumor Image Dataset
https://www.kaggle.com/navoneel/brain-mri-images-for-brain-tumor-detection