

A PROJECT REPORT
ON
“BRAIN TUMOR DETECTION USING BLOCKCHAIN”

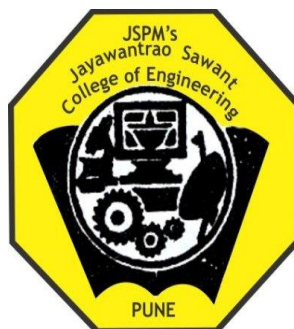
SUBMITTED TO THE SAVITRIBAI PHULE PUNE UNIVERSITY,
PUNE. IN PARTIAL FULFILLMENT OF THE REQUIREMENTS
FOR THE AWARD OF THE DEGREE

BACHELOR OF ENGINEERING (Computer Engineering)

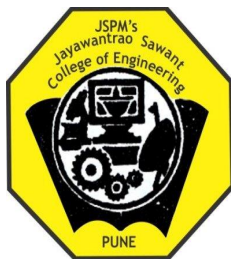
BY

MR. TEJAS KHAIRNAR	Seat No:B190404263
MR. NIRAJ OHOL	Seat No:B190404301
MR. YASH ZOPE	Seat No:B190404367

UNDER THE GUIDANCE OF
PROF. GANGA YADAWAD



DEPARTMENT OF COMPUTER ENGINEERING
JSPM's Jayawantrao Sawant College of Engineering
Hadapsar, Pune-28.
[2022-23]



DEPARTMENT OF COMPUTER ENGINEERING
JSPM's Jayawantrao Sawant College of Engineering
Hadapsar, Pune-28.

CERTIFICATE

This is to certify that the seminar report entitled
“Brain Tumor Detection using Blockchain”

Submitted by
MR. TEJAS KHAIRNAR Seat No:B190404263
MR. NIRAJ OHOL Seat No:B190404301
MR. YASH ZOPE Seat No:B190404367

is a bona-fide work carried out under the supervision of **Prof. Ganga Yadawad**
and it is submitted towards the partial fulfillment of the requirement of
Savitribai Phule Pune University, Pune for the award of the degree of Bachelor
of Engineering (Computer Engineering) Project.

Prof. Ganga Yadawad
Internal Guide
Dept. of Computer Engg.

Dr. Poonam Lambhate
H.O.D
Dept.of Computer Engg.

Prof. Nitin Zinzurke
Project Co-ordinator
Dept. of Computer Engg.

External Examiner
Place :
Date :

Dr. R. D. Kanphade
Principal
JSCOE HADAPSAR

Acknowledgments

It gives us great pleasure in presenting the preliminary project report on
‘Brain Tumor Detection using Blockchain’.

*We would like to take this opportunity to thank our internal guide and Head of computer engineering department **Prof. Ganga Yadawad** for giving us all the help and guidance we needed. We are really grateful to her for her kind support. Her valuable suggestions were very helpful.*

TEJAS KHAIRNAR
NIRAJ OHOL
YASH ZOPE
(B.E. Computer Engg.)

Abstract

Brain tumor can be classified into two types: benign and malignant. The brain tumors, are the most common and aggressive disease, leading to a very short life expectancy in their highest grade. Thus, treatment planning is a key stage to improve the quality of life of patients. Generally, various image techniques such as Computed Tomography (CT), Magnetic Resonance Imaging (MRI) and ultrasound image are used to evaluate the tumor in a brain, lung, liver, breast, prostate...etc. Especially, in this work 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. But it having some limitation (i.e) accurate quantitative measurements is provided for limited number of images. Hence trusted and automatic classification scheme are essential to prevent the death rate of human.

The Block chain technology is the emerging field of science, which impart a major role in every application area of science, which includes the education, Banking, and health care also. In health care most of the health issues are occur due to because of their negligence of proper diagnosis by the doctor and ignorance the symptom by patients. The most common disease now a day is called as tumor . The brain tumor is usually having a symptom like increase in headache frequently, unexplained nausea or vomiting. Sometimes it may also have blurred vision, double vision and sometimes loss of peripheral visions are also. In this project we are going to diagnose the tumor using the Blockchain strategy.

Contents

1	INTRODUCTION	09
2	LITERATURE SURVEY	11
3	PROPOSED SYSTEM	14
3.1	Problem Statement	15
3.2	Objectives	15
3.3	Scope of Project	16
4	SOFTWARE REQUIREMENTS & SPECIFICATIONS	17
4.1	Software Requirements	18
4.3	Software Quality Attributes	18
5	SYSTEM DESIGN & PROJECT PLAN	19
5.1	Data Flow Diagrams	20
5.1.1	DFD Level 0	20
5.1.2	DFD Level 1	21
5.2	UML Diagrams	22
5.2.1	Use Case Diagram	22
5.2.2	Class Diagram	23
5.2.3	Activity Diagram	24
5.2.4	Sequence Diagram	25
5.3	Project Plan	27
6	SYSTEM ARCHITECTURE	30
6.1	Architecture Diagram	31
6.2	Methodology	34

6.3 Algorithms	37
7 RESULTS AND ANALYSIS	39
7.1 Implementation	40
7.2 Testing.....	41
7.3 Analysis.....	44
8 ADVANTAGES, LIMITATIONS & APPLICATIONS	49
8.1 Advantages.....	50
8.2 Limitations	51
8.3 Applications	52
9 CONCLUSION	43
10 FUTURE SCOPE	55
11 BIBLIOGRAPHY	57
ANNEXURE I	60
Published Paper	
ANNEXURE II	66
Certificates	
ANNEXURE III	69
Base Papers	

List of Figures

5.1.1	DFD Level – 0	21
5.2.1	Use case Diagram	22
7.5.1	Time Processing Chart	25
5.2.2	Class Diagram	23
5.2.4	Sequence Diagram	25
5.3.1	Timeline Chart	28
6.1.1	System Overview	32
7.3.1	Waterfall Model	44
7.3.2	Component Diagram	45

List of Tables

5.3.1	Project Stage	27
5.3.2	Time Line Chart	29
6.2.1	Time Processing Chart	48

CHAPTER 1

INTRODUCTION

1. Introduction

The big problem of the tumors are life threatening. Essential brain tumors originate within the brain. In the optional sort of brain tumor, the tumor venture inside the brain effects from different pieces concerning the body. Imaging tumors besides further precision assumes a critical job in the conclusion of tumors. It includes high-goals systems like MRI, CT, PET, and so forth. MRI is a significant method for examining the body's instinctive arrangements . It is broadly utilized because it provides better quality images regarding the brain and malignant tissues contrasted and different therapeutic imaging procedures, for example, X Beam or Figured Tomography (CT). Almost like a nonabrasive procedure tomography is considerably used . the elemental rule behind MRI is to provide pictures from MRI checks utilizing a solid magnetic discipline furthermore radio entrances of the body that assists in watching the expansion regularities of the body.

Image Segmentation signifies a procedure of partitioning a picture within its elector parts or things among specific image for associate example created from pixels, pixels throughout the venue are comparable as indicated by some homogeneity criteria, for example, shading, power or surface so as to search out and acknowledge limits in an image . within the course of the previous few decades, tons of endeavors are concentrating on the segmentation procedure.

CHAPTER 2

LITERATURE SURVEY

- **Literature Survey:**

In this section, we present a review of related works on detection of brain tumor applying deep learning procedures. The variety of automatic ways of segmentation of CNN -dependent brain tumors was recently presented. Along these lines, the 4D computer file is adequately served by CNN. While handling high dimensions can additional easily speak to the 3D plan of organic structures, it also builds up the pile of network preparation. 2 distinctive networks are structured. The start was a four-level CNN that contained the information coverage containing fifteen 3D channels with fifty three abstraction measures , with ANN additional fourth measurement representing the associated MRI methodology, which resulted in a channel state of five x 5 x 5 x 4. Two of the channels with hidden layers have an extra 53 spatial measurements additionally to a measurement related to the quantity of channels within the previous layer. In particular, the amount of channels was a deep level 25.

The end coverage includes the Soft max course 6 courses ordered during any tissue kind in order to get the understanding of the yield as probabilities. The following network is much indistinguishable, with the exception of AN additional hidden layer with forty channels of size 53. Associated parts are used for preprocessing the results. In

[13], Zikic et al. developed an understanding strategy to modify the 4D knowledge with the aim that Paradigm 2D-CNN styles will be used to increase the load of the high dimensional CNN structure whereas increasing computational productivity. The reconnaissance is completed by ever-changing all 4- modalities of the 3D input of the size (d1 x d2 x d3 x 4) to 4. d3- channel of second patches of size (d1 x d2 x 4d3). With this strategy, input patches of size 19x19x4 in an exceedingly 2D-CNN with 2 convolutional layers with sixty four channels with a size of 5 x five x 4 and three x 3 x 4 are nourished individually, isolated by a most pooling layer, followed of a fully associated (FC) layer and a soft max layer.

In [14], another similar approach described as in [16]. In addition to this novel composition method, a production is also carried out in two stages. Keep away from uneven characters within the class. In the main phase Fell CNN is ready with an adequate acquisition of teams , including the following phase. CNN was retraining with increasing delegate dissemination of the first metaphors. In addition, the Max out nonlinearity was used and the strategy the associated phase was updated as post handling action. High Minxes Cubes rates of 88% on the entire growth area, 79% throughout Center Tumor District and 73% for the dynamic tumor venue are taken into account.

In [15] a limited design for CNN is suggested throughout the approach. Instead of using CNNs to characterize focal voxels with respect to data image items within brain tissue classes, initial fixings of names are extracted from sand exactitude patterns and then bundled by k-implied algorithmic rule in N assemblies to border an N size marker fix40a4lexicon. Then a second CNN is used to characterize

multi-level knowledge model pieces at intervals a unit of these assemblies. In relation to this segmentation implementation of the schema, Whelps cubes rates of 83%, 75% and 77% for of the entire growth, the central tumor and the dynamic tumor areas are considered separately.

In [18], Rao et al. In addition, several level fixes for each element from four different CNN individual search info bits were created from each different MRT methodology image. The fixtures from the last rock bottom of CNNs were successfully connected and used as highlight maps to create an RF classifier% was given in this way.

In [20] another innovative approach that was carried out was carried out in two CNN architectures. By extracting smaller patches and larger calculable fixes at the same time, a Fell CNN that processes near intricacies of the brain tomography is found in addition to the larger setting of the brain tissue in an exceedingly similar space of the image, patches are estimated and 33 x thirty three elements are made by each distinctive MRI -Method for the nearby path separated, and patches with a size of 65 x 65 are extracted for the worldwide path to rearrange the marking of the focal pixel CNN to yield patches of size 33 x 33 x 5. Those yield patches were later linked with the neighborhood patches of size 33x33x4 and nourished as a data to a two-track CNN with convolutional stages contain 7 x 7 estimated channels in a single way and 13 x 13 measured channels in the previous one. Consequently, making fell two-pathway CNN architecture. A few altered architectures of this fell CNN process was likewise planned.

CHAPTER 3 PROPOSED SYSTEM

3.1 Problem Statement :

Traditionally, the diagnosis of brain tumors involves a team of medical professionals who interpret the patient's symptoms and medical imaging results. However, misdiagnosis and delayed diagnoses are still common, which can lead to serious consequences for patient. By using blockchain technology, the diagnostic process can be made more accurate and transparent. Medical imaging results can be recorded and verified on a decentralized network, allowing for a more accurate diagnosis. Additionally, the use of smart contracts can help ensure that medical professionals are following established protocols and procedures, further improving the accuracy of the diagnosis.

Furthermore, the use of blockchain can improve the security and privacy of patient data. Medical records are often vulnerable to hacking and theft, but the use of blockchain can ensure that patient data is protected and only accessible to authorized individuals. Overall, the use of blockchain in brain tumor detection has the potential to improve the accuracy, security, and transparency of the diagnostic process, ultimately leading to better patient outcomes.

Problem Definition: The diagnosis of brain tumors is a critical medical procedure that requires accurate interpretation of medical imaging results. Misdiagnosis or delayed diagnosis of brain tumors can lead to serious consequences for patients. Additionally, the security and privacy of patient data are important concerns in the medical field.

3.2 Objectives :

The main objective of this project is to develop a system that utilizes blockchain technology to improve the accuracy, security, and transparency of the brain tumor detection process. Specifically, the project aims to:

1. Develop a decentralized network for recording and verifying medical imaging results, improving the accuracy of the diagnosis.
2. Implement smart contracts to ensure that medical professionals are following established protocols and procedures, further improving the accuracy of the diagnosis.
3. Improve the security and privacy of patient data by utilizing blockchain technology.
4. Create a user-friendly interface for medical professionals to easily access and interpret medical imaging results

3.3 Scope of Project

The scope of this project is to develop a blockchain-based system for brain tumor detection that includes the following components:

A decentralized network for recording and verifying medical imaging results.

Smart contracts to ensure that medical professionals are following established protocols and procedures.

1. Improved security and privacy of patient data.
2. A user-friendly interface for medical professionals to access and interpret medical imaging results.
3. The project will focus on the development of a proof-of-concept system that demonstrates the potential of blockchain technology in improving the accuracy, security, and transparency of the brain tumor detection process.

CHAPTER 4

SOFTWARE REQUIREMENTS & SPECIFICATIONS

4.1 Software Requirements

- Operating system : Windows 10.
- Coding Language : Python
- IDE : Python IDEL
- Packages : Flask, OpenCV, Tensorflow, keras

3.2 Software Quality Attributes

- The system considers following non-functional requirements to provide better functionalities and usage of system.
- **Availability:** The system is available during 24 hours of a day.
- **Usability:** The system is designed keeping in mind the usability issues considering the end-users who are developers/programmers. It provides detailed help which would lead to better and faster learning. Navigation of system is easy.
- **Consistency:** Uniformity in layout, screens, Menus, colors scheme, format.
- **Performance:** The performance of the system is fast and as per user requirement. From this system gives expected outcome in less time and less space since efficiency is higher. Speed is totally depending on the response of the database and connection type.
- **Extendibility:** Prevention in the system is done by the system only, in which we make changes in the system later on.
- **Reusability:** Files of any type can be used by the system for any number of times during transformation.
- **Reliability:** Protection of data from malicious attack or unauthorized access.
- **Security:** The system provides security to the randomly generated private key by performing encryption to it for encrypting patient data and thus protects from other nodes in the network. The network is free from malicious node and misbehaving node attacks.

CHAPTER 5

SYSTEM DESIGN & PROJECT PLAN

5.1 Data Flow Diagrams / UML Diagram

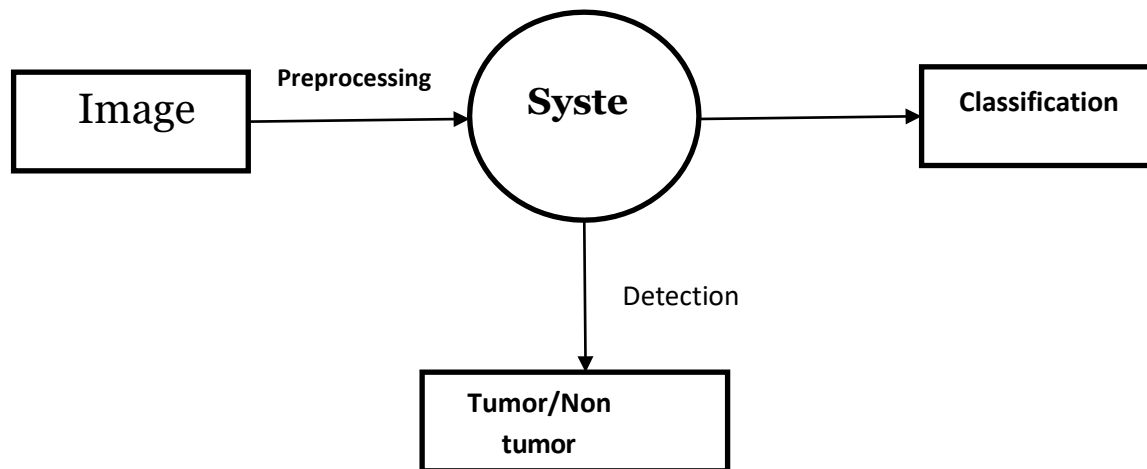


Fig.5.1.1. Data Flow Diagram

The requirements section of hardware includes minimum of 100 GB hard disk and 4 GB RAM with 1 GHz or higher speed. The primary requirements include a memory of 1 GB for the application of python and MySQL (If required). User interface of this program is the common windows interface, nothing additional is required. The System user interface should be intuitive, such that 99.9% of all new system users are able to use Proposed System application without any assistance. User registered in to system and log in then input to system as gesture and wait for response for system. User interacts with the android application.

5.1.1 DFD 0

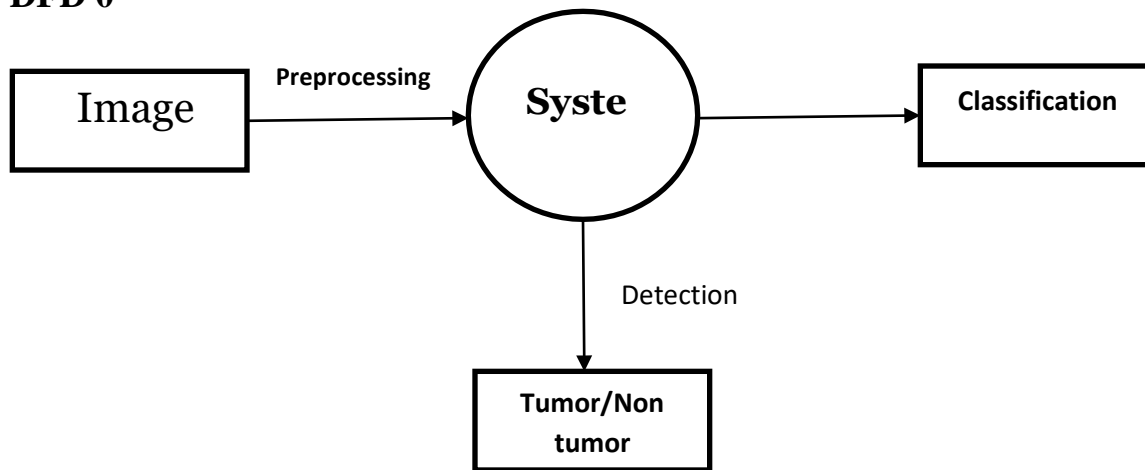


Fig.5.1.1.DFD0

- The application is user friendly.
- It provides an easy interface to user.
- The accessibility or response time of the application should be fast.
- Performance of the system is appropriate.
- The Functional Requirements Specification documents the operations and activities that a system must be able to perform. Functional Requirements should include:
 - Dataset must be required
 - Input will be must required
- The Functional Requirements Specification is designed to be read by a general audience. Readers should understand the system, but no particular technical knowledge should be required to understand the document.

5.2 UML Diagrams

5.2.1 Use case Diagram:

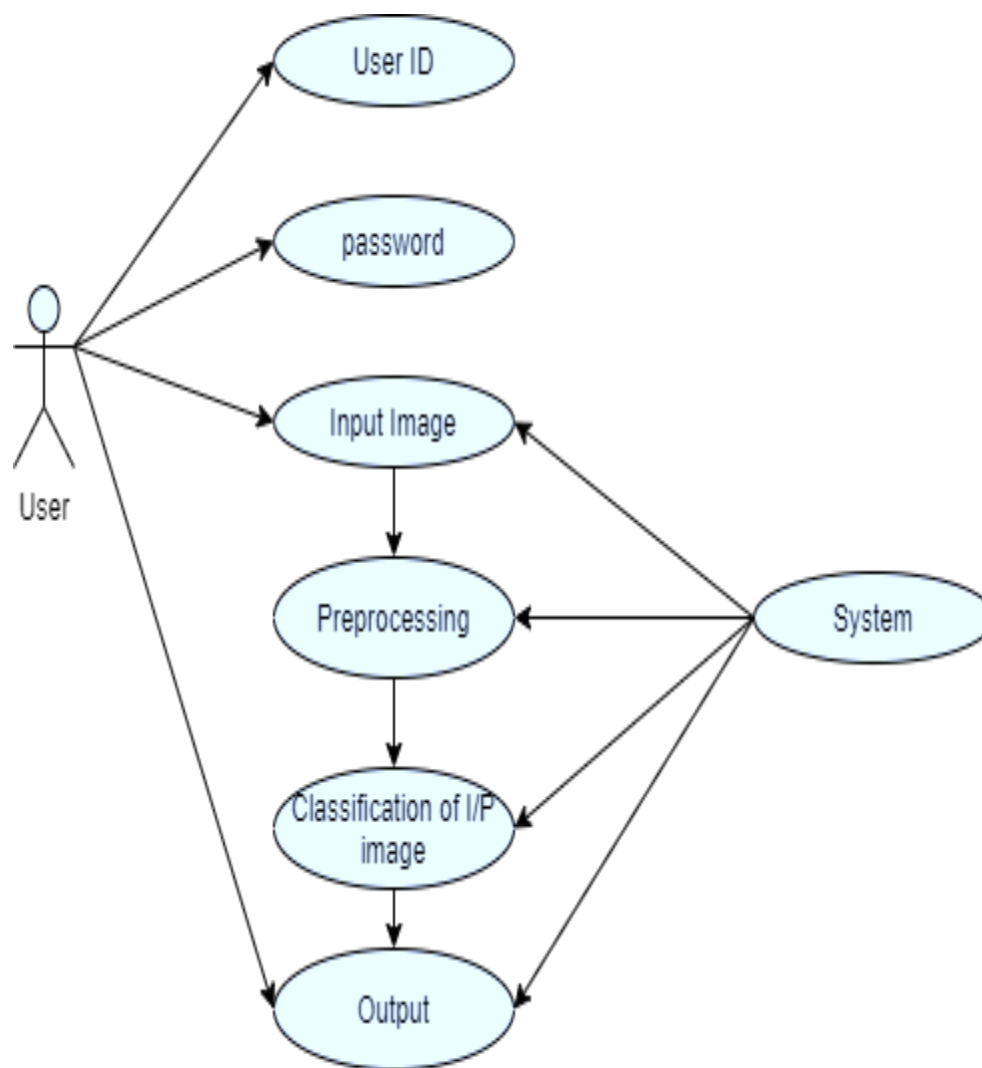


Fig.5.2.1 use case diagram of brain tumor detection system

The requirements section of hardware includes minimum of 100 GB hard disk and 4

GB RAM with 1 GHz or higher speed. The primary requirements include a memory of 1 GB for the application of python and MySQL (If required). User interface of this program is the common windows interface, nothing additional is required. The System user interface should be intuitive, such that 99.9% of all new system users are able to use Proposed System application without any assistance. User registered in to system and log in then input to system as gesture and wait for response for system. User interacts with the android application.

5.2.2 Class Diagram:

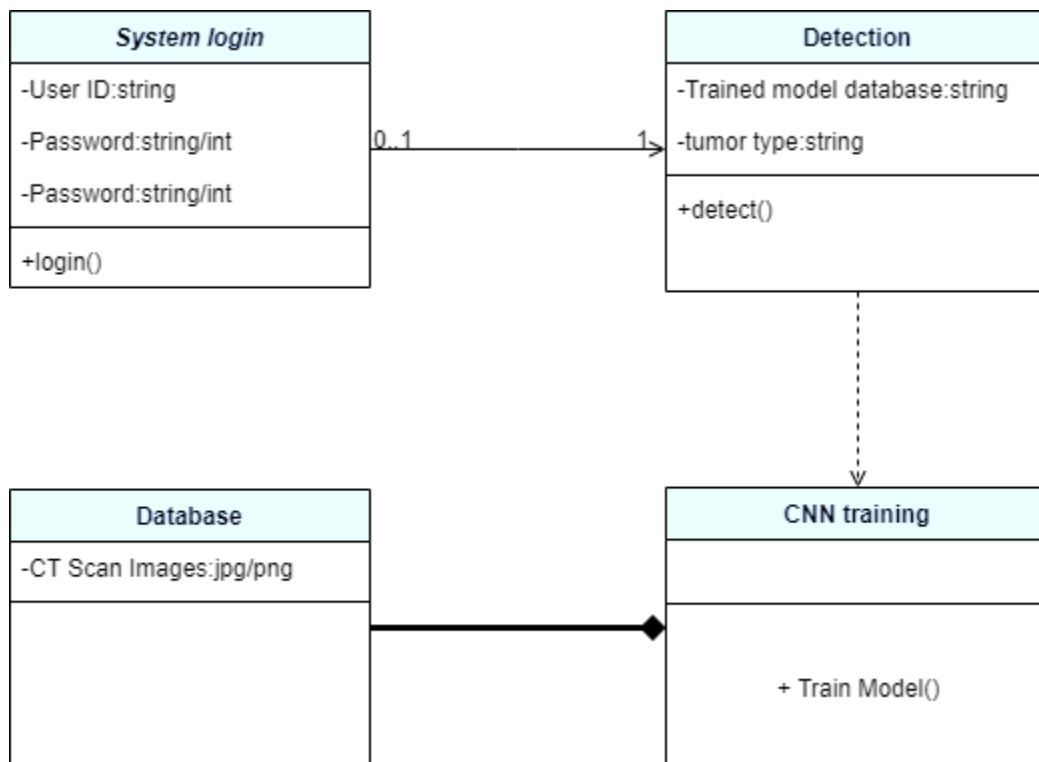


Fig.5.2.2 Class diagram of the system

5.2.3 Activity diagram of the system

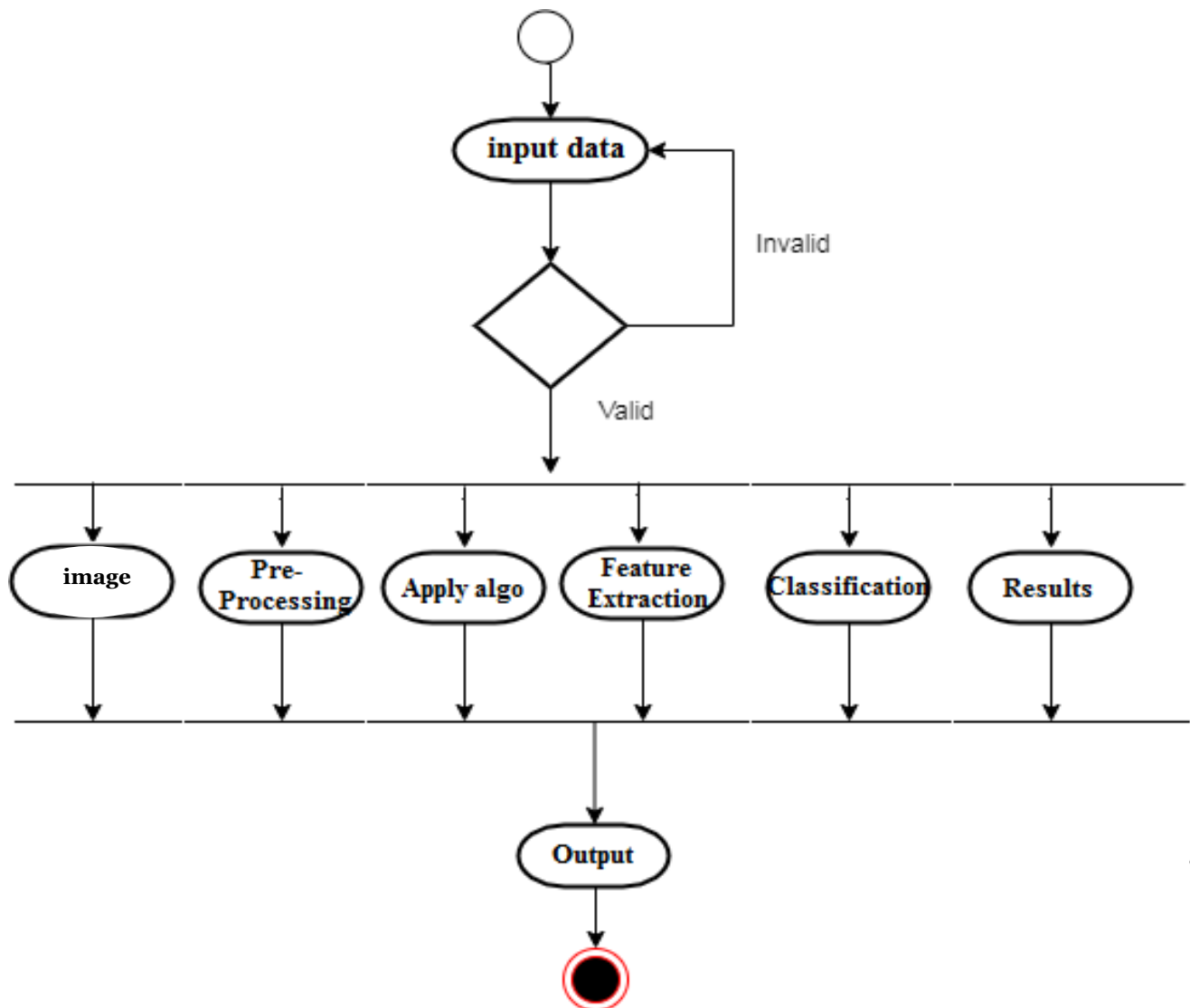


Fig.5.2.3 Activity diagram of the system

The computer this software going to be install need to have python IDE equal or above, Windows 7. On that Windows platform python, python version 3.* will be installed and that will be the platform the particular software will be run. There willbe an python IDE data transmission

5.2.4 Sequence Diagram:

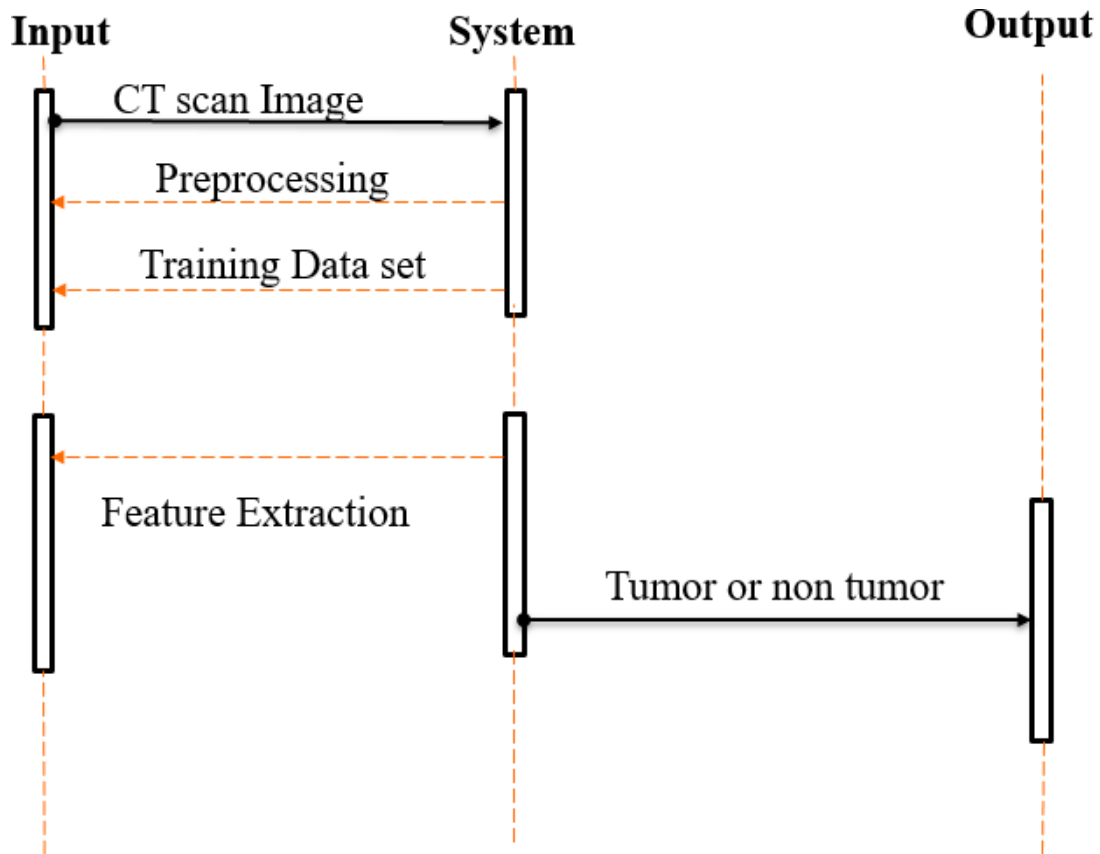


Fig.5.2.4 Sequence Diagram of brain tumor detection system

Communication architecture defines the frequency and fidelity of information flow between individuals in your organization. It helps structure how and when you communicate, both within a team and cross-functionally. The specific tactics are unique to each organization, but it requires proactive thought and investment

5.2.5 Flow Chart of the System

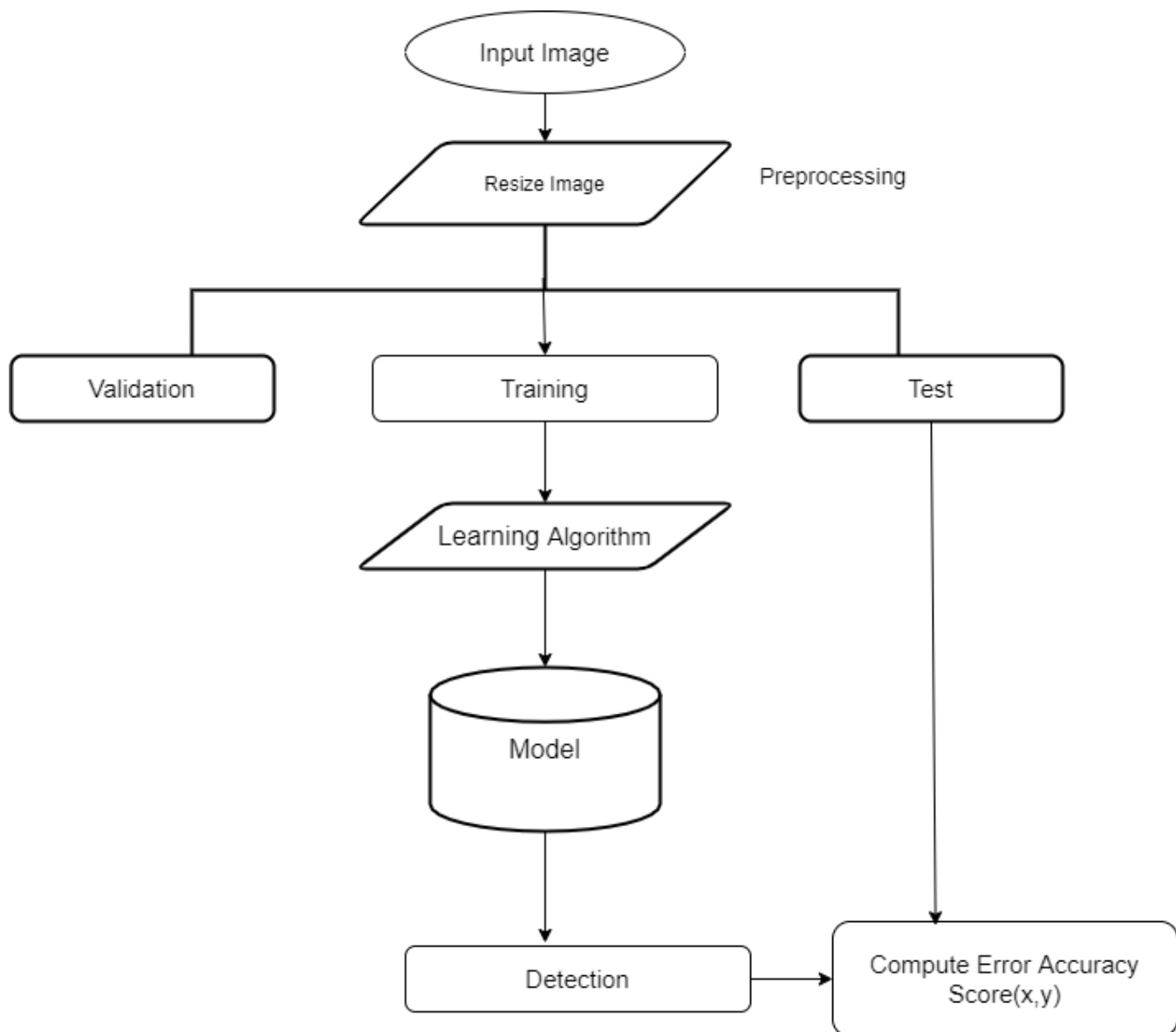


Fig 5.2.5 Flowchart of brain tumor detection

5.3PROJECT SCHEDULE

Project task set

Major Tasks in the Project stages are:

Priority (High to low)	Risks	Back-up plan
1	Schedule	Overtime
2	Operational	Validation
3	Business	Marketing
4	Technical	-

- Task 1: Requirement Gathering
- Task 2: Literature Survey
- Task 3: System Design
- Task 4: Functionality Implementation
- Task 5: Testing

5.3.1 Timeline Chart



Figure 5.3.1: Timeline Chart

5.3.2 TEAM ORGANIZATION

Team Structure

Whatever activities are done related to the project that we all showing all details log to our guide. All the reporting are noted to the guide.

Work Task	Description	Duration
Literature Search	Related work done for conceptual data similarity	6 weeks
System analysis	Critical analysis and comparison of technologies studied and results achieved in research	4 weeks
Design and Planning	Modeling and design and dataset searching or creation	8 weeks
Implementation	Divided into phases	
Phase A	Implementation module 1	2 weeks
Phase B	Implementation module 2	2 weeks
Phase C	Implementation module 3	2 weeks
System Testing	Test system quality, fix errors if any and improve if needed. Test system for different data sets	3 weeks
Final Report	Prepare and upload Initial Report	2 weeks
Initial Report	Prepare and upload Initial Report	2 weeks

Table 5.3.2: Time line Chart

CHAPTER 6

SYSTEM

ARCHITECTURE

6.1 SYSTEM ARCHITECTURE

CT scan mostly depends on computer technology to generate or display digital images of the internalorgans of the human body which helps the doctors to visualize the inner portions of the body. A CT

scan combines sophisticated x-ray and computer technology. CT can show a combination of soft tissue, bone, and blood vessels. CT images can determine some types of tumors, as well as help detect swelling, bleeding, and bone and tissue calcification. Usually, iodine is the contrast agent used during a CT scan.

The CT scan image of brain tumor is an input for this proposed algorithm. The CT scan image is a blur image. The noise is present in this image. Noise disturbances may cause because of electronic imaging sensors, sensor temperature, insufficient Light levels, film granularity, and channel noise. So preprocessing is essential for such images to remove blurriness from it and make it sharper

• Overall Architecture Design

We propose CT Scan image quality enhancement and its application using CNN Algorithm. For developing dependable and ordinary techniques to identify the brain tumor, extract the quality of it for medicinal determination, visualization, and the presence forecast. IT is Robust and scalable CNN based image segmentation and features extraction by considering different types of the dataset with minimum computation efforts. The use of appropriate feature extraction and reduction models may help to reduce the detection time and improving the accuracy.

1.CT scan

CT scan mostly depends on computer technology to generate or display digital images of the internalorgans of the human body which helps the doctors to visualize the inner portions of the body. A CT

scan combines sophisticated x-ray and computer technology. CT can show a combination of

soft tissue, bone, and blood vessels. CT images can determine some types of tumors, as well as help detect swelling, bleeding, and bone and tissue calcification. Usually, iodine is the contrast agent used during a CT scan. The CT scan image of brain tumor is an input for this proposed algorithm. The CT scan image is a blur image.

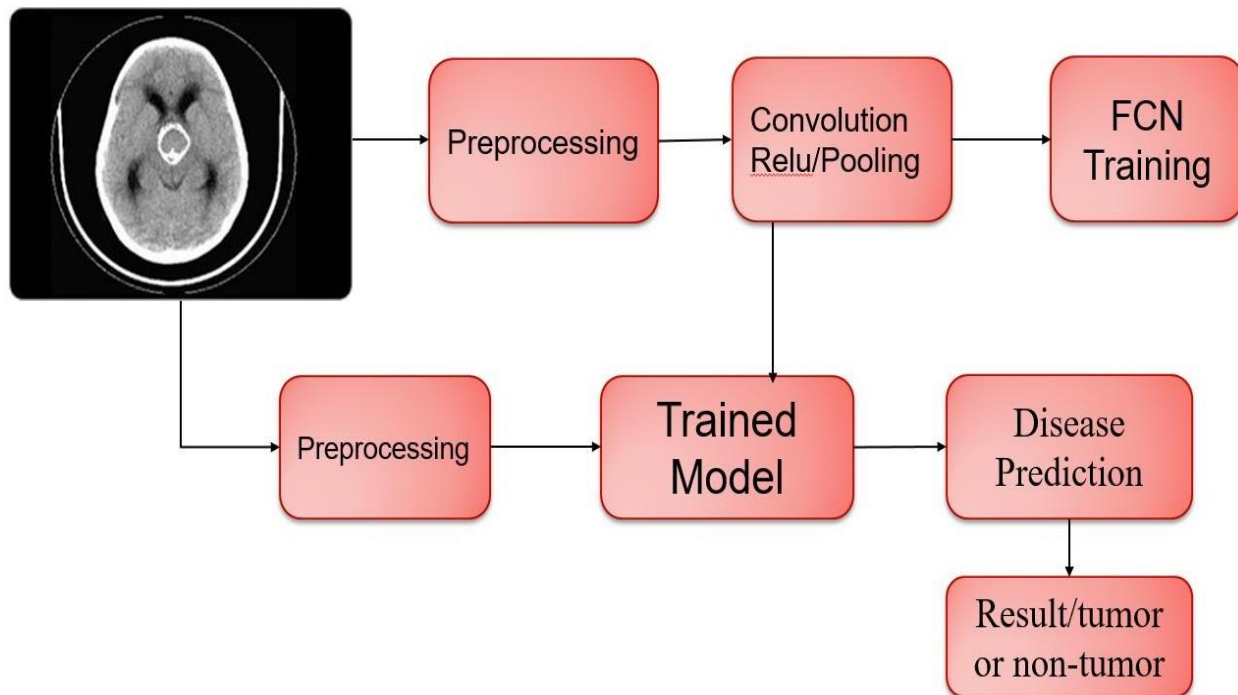


Fig 6.1. Architecture of Brain Tumor Detection system

The noise is present in this image. Noise disturbances may cause because of electronic imaging sensors, sensor temperature, insufficient Light levels, film granularity, and channel noise. So preprocessing is essential for such images to remove blurriness from it and make it sharper.

2.Preprocessing

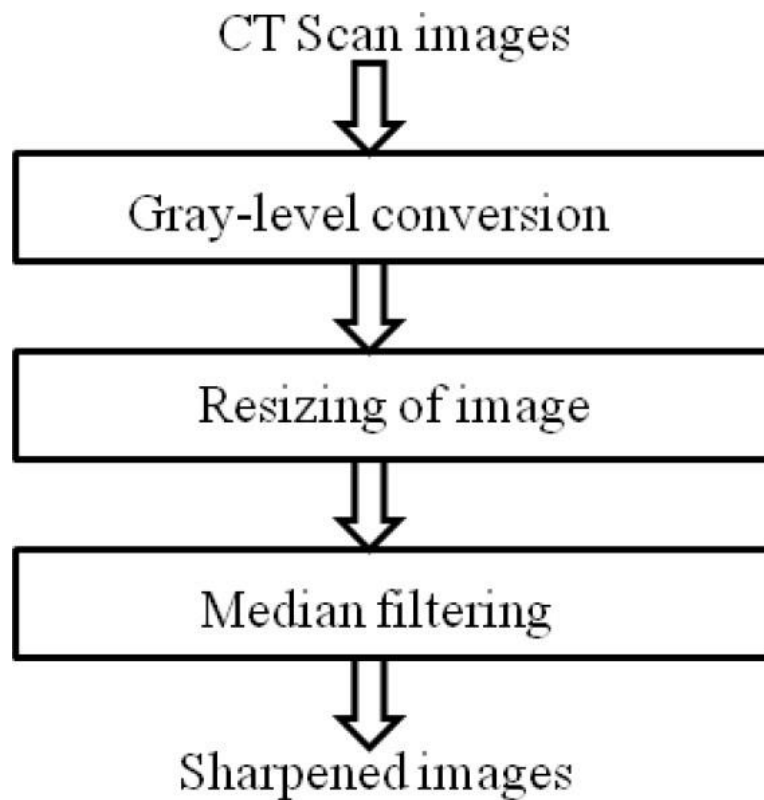


Fig.6.2.1 Steps of Preprocessing

3.Tumors Area calculation

Area of an image is calculated by knowing the vertical and horizontal resolution of an image. It depends on the three key factors:

1. Total no of pixel in region of interest
2. Horizontal resolution
3. Vertical resolution

6.2 Methodology

In this study, to improve the performance and reduce the complexity involves in the CT scan image. Brain tumors can be detected manually by experts from the CT scan images we apply Preprocessing on that and show the accurate result.

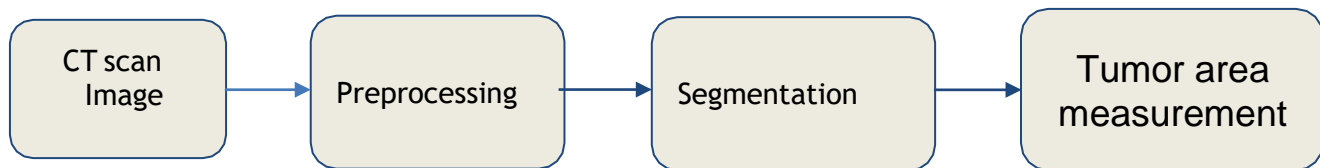


Fig6.2.2 Methodology of Brain Tumor Detection

1. CT scan Image:

The term “computed tomography”, or CT, refers to a computerized x-ray imaging procedure in which a narrow beam of x-rays is aimed at a patient and quickly rotated around the body, producing signals that are processed by the machine’s computer to generate cross-sectional images or “slices” of the body. These slices are called tomographic images and contain more detailed information than conventional x-rays. Once a number of successive slices are collected by the machine’s computer, they can be digitally “stacked” together to form a three-dimensional image of the patient that allows for easier identification and location of basic structures as well as possible tumors or abnormalities.

2. Preprocessing

Successful Segmentation of the image is followed by the post-processing of the image. Pre- Processing of the image involves steps to judge the size of the tumor and its type. Pre-processing may also involve various optimization techniques to further improve the result.

Camera failure:if camera stops working then there will be not capturing of images and system has no inputs for further operations

Monitor failure:system will not work properly. And access is not given to user properly.

Camera failure:camera fails due to high voltage supply or internal hardware issues.

Monitor failure:monitor fails due to damage of display sensors responsible for displaying

1. Research and analyze the current methods of brain tumor detection and identify the limitations and challenges of the existing systems.
2. Study the basics of blockchain technology and its potential applications in the medical field.
3. Design and develop a decentralized network for recording and verifying medical imaging results using blockchain technology.
4. Develop smart contracts to ensure that medical professionals are following established protocols and procedures.
5. Implement encryption and security protocols to ensure the confidentiality and privacy of patient data.
6. Create a user-friendly interface for medical professionals to access and interpret medical imaging results.
7. Test the system with simulated medical imaging data to evaluate the accuracy and efficiency of the system.
8. Conduct user testing with medical professionals to evaluate the usability and effectiveness of the system.
9. Analyze the results and make improvements to the system based on the feedback received from medical professionals.

OVERVIEW OF PROJECT MODULES

1. F1: Process the captured medical imaging results and record on a network
2. Algorithm: capture medical imaging results, record on decentralized network
3. Input: medical imaging results
4. Output: recording on decentralized network

$C = \{mi\}$ Where C is the dataset of medical imaging results(mi).

Steps: Capture medical imaging results (e.g. MRI or CT scan).

1. Process the medical imaging results to identify any potential brain tumors.
2. Record the medical imaging results on a decentralized network using blockchain technology.
3. Verify the medical imaging results on the decentralized network to ensure accuracy.
4. Store the verified medical imaging results securely on the blockchain network .
5. Provide access to authorized medical professionals to view and interpret the verified medical imaging results.
6. Detection of unknown person

6.3 ALGORITHM DETAILS

- CNN (Convolutional Neural Network) is a deep learning algorithm that has shown great success in image recognition tasks, including medical image analysis. In the context of Brain tumor detection using blockchain technology, CNNs can be used to analyze medical imaging results and identify potential brain tumors.
- Here's how CNN algorithm can be used in Brain tumor detection using blockchain technology:
- Preprocessing the medical imaging results: The medical imaging results, such as MRI or CT scans, are preprocessed to extract the relevant features of the image. This includes resizing the images, normalizing the pixel values, and applying various image enhancement techniques to improve the image quality.
- Training the CNN model: Once the medical imaging results are preprocessed, they are used to train a CNN model. This involves feeding the preprocessed images into the CNN model, along with their corresponding labels (i.e. whether they contain a brain tumor or not). The CNN model then learns to recognize the patterns and features that distinguish brain tumors from normal brain tissue.
- Testing the CNN model: After the CNN model is trained, it is tested on a separate set of medical imaging results to evaluate its performance. This involves feeding the preprocessed images into the CNN model and comparing its predictions to the true labels of the images. The performance of the CNN model is evaluated using various metrics such as accuracy, sensitivity, and specificity.
- Integrating the CNN model with blockchain technology: Once the CNN model is developed and tested, it can be integrated with blockchain technology to record and verify the medical imaging results on a decentralized network. The medical imaging results can be processed by the CNN model to identify any potential brain tumors and the results can be recorded on the blockchain network. The blockchain network can be used to store the verified medical imaging results securely and provide access to authorized medical professionals to view and interpret the results.

Segmentation

Segmentation technique is to separate out tumor region from CT scan image. Using segmentation it is possible to identify objects, boundaries, location in an image. There are many applications of segmentation in medical field like identify the diseases in CT scan. The segmentation is done by Region growing method and edge detection method.

Steps of Proposed algorithm is given below:

- Step1. -Input CT scan Image for detection
- Step2. -Noise removal and blur removal.
- Step3. -Generate feature vector.
- Step4. -Calculate the Euclidean distance between the input vector and previously stored vector.
- Step5. -For the accuracy of the result, define threshold level.
- Step6. -Find out those images which have Euclidean distance lesser than upper cut limit.
- Step7. -Compare features images from step6 to the features of a tumor image.
- Step8. -Suggesting result is tumor or non-tumor.

CHAPTER 7

RESULTS & ANALYSIS

7.1 Implementation:

In implementation phase of our project we have implemented various modules required of successfully getting expected outcome at the different module levels. With inputs from system design, the system is first developed in small programs called units, which are integrated in the next phase. Each unit is level-opened and tested for its functionality which is referred to as Unit Testing.

- **Testing:**

The different test cases are performed to test whether the project modules are giving expected outcome in assumed time. All the units developed in the implementation phase are integrated into a system after testing of each unit. Post integration the entire system is tested for any faults and failures.

- **Deployments of System:**

Once the functional and non-functional testing is done, the product is deployed in the customer environment or released into the market.

- **Maintenance:**

There are some issues which come up in the client environment. To fix those issues patches are released. Also to enhance the product some better versions are released. Maintenance is done to deliver these changes in the customer environment. All these phases are cascaded to each other in which progress is seen as flowing steadily downwards like a waterfall through the phases. The next phase is started only after the defined set of goals are achieved for previous phase and it is signed off, so the name "Waterfall Model". In this model phases do not over

7.2 TYPE OF TESTING

.

Type Of Testing Used :

Along with the type of testing also mention the approach to be followed for the testing, that is, Manual Testing or Automated Testing. Use Automated Testing Plan for planning automation activities in details. The different types of testing that may be carried out in the project are as follows:

• Unit Testing:

Individual components are tested independently to ensure their quality. The focus is to uncover errors in design and implementation, including

- Data structure in component
- Program logic and program structure in a component
- Component interface
- Functions and operations of a component

• Integration Testing :

A group of dependent components are tested together to ensure their quality of their integration unit. This approach is to do incremental integration to avoid “bigbang” problem. That is when the entire program is put together from all units and tested as a whole. The big-bang approach usually results in chaos which incremental integration avoids. Incremental integration testing can be done in two different way top down and bottom up. Then there is also the possibility of regression integration.

The top down integration is when modules are integrated by moving downwards through the control hierarchy, beginning with the main control module. Modules subordinate to the main control module are incorporated into main structure in either depth-first or breadth-first manner. The top down integration verifies major controls or decision points early in the test process. If major control problems do exist

- Design and construction of software architecture
- Integrated functions or operations at sub-system level – Interfaces and interaction and/or environment integration

• **System Testing :**

The system software is tested as a whole. It verifies all elements mesh properly to make sure that all

system functions and performance are achieved in the target environment. The focus areas are:

- System functions and performance
- System reliability and recoverability (recovery test)
- System behavior in the special conditions (stress and load test)
- System user operations (acceptance test/alpha test)
- Hardware and software integration collaboration – Integration of external software and the system.

• **Validation Testing:**

Validation can be defined in many ways, but a simple definition is that succeeds when software functions in a manner that can be reasonably expected by the customer. Software validation is achieved through a series of black box tests that demonstrate conformity with requirements. A test plan outlines the classes of tests to be conducted and a test procedure defines specific test cases that will be used to demonstrate conformity with requirements. Both the plan and procedure are designed to ensure that all functional requirements are satisfied, all behavioral characteristics are achieved, all performance requirements are attained, documentation is correct, and human engineered and other requirements are met.

• **White Box Testing:**

White-box test design allows one to peek inside the “box”, and it focuses specifically on using internal knowledge of the software to guide the selection of test data. Synonyms for white-box include: structural, glass-box and clear-box.

White box testing is much more expensive than black box testing. It requires the source code to be produced before the tests can be planned and is much more laborious in the determination of suitable input data and the determination if the software is or is not correct. This testing is concerned only with testing the software product; it cannot guarantee that the complete specification has been implemented.

• **Black Box Testing:**

Black-box test design treats the system as a “black-box”, so it doesn’t explicitly use knowledge of the internal structure. Black-box test design is usually described as focusing on testing functional requirements. Synonyms for black box include:behavioral,

functional, opaque-box, and closed-box. Black box testing is concerned only with testing the specification; it cannot guarantee that all parts of the implementation have been tested. Thus black box testing is testing against the specification and will discover faults of omission, indicating that part of the specification has not been fulfilled.

- **GUI Testing:**

Graphical User Interface (GUIs) present interesting challenges for software engineers. Because of reusable components provided as part of GUI development environments, the creation of the user interface has become less time consuming and more precise. But, the same time, the complexity of GUIs has grown, leading to more difficulty in the design and execution of the test cases. Because many modern GUIs have the same look and same feel, a series of test cases can be derived.

- **Unit Testing:**

It is the testing of individual software units of the application .it is done after the completion of an individual unit before integration. Unit testing involves the design of test cases that validate that the internal program logic is functioning properly, and that program inputs produce valid outputs. All decision branches and internal code flow should be validated. This is a structural testing, that relies on knowledge of its construction and is invasive.

Unit tests perform basic tests at component level and test a specific business process, application, and/or system configuration. Unit tests ensure that each unique path of a business process performs accurately to the documented specifications and contains clearly defined inputs and expected results.

7.3 ANALYSIS

We are using waterfall model:

- **Requirement gathering and analysis:**

In this step of waterfall we identify what are various requirements are need for the project such are software and hardware required, database, and interfaces.

- **System Design:**

In this system design phase we design the system which is easily understood for end user i.e. user friendly. We design some UML diagrams and data flow

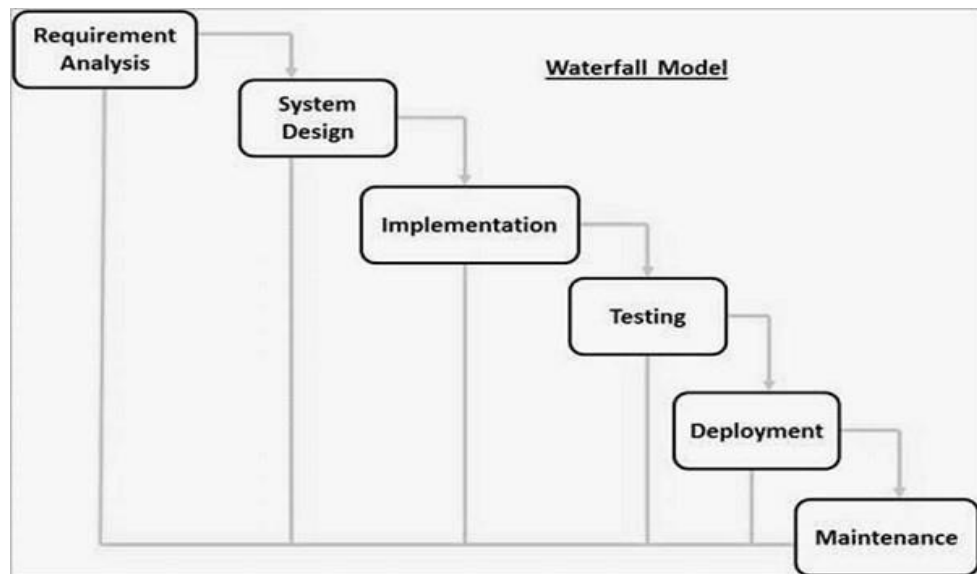


Fig. 7.3.1: Waterfall Model

diagram to understand the system flow and system module and sequence of execution.

Package Diagram:

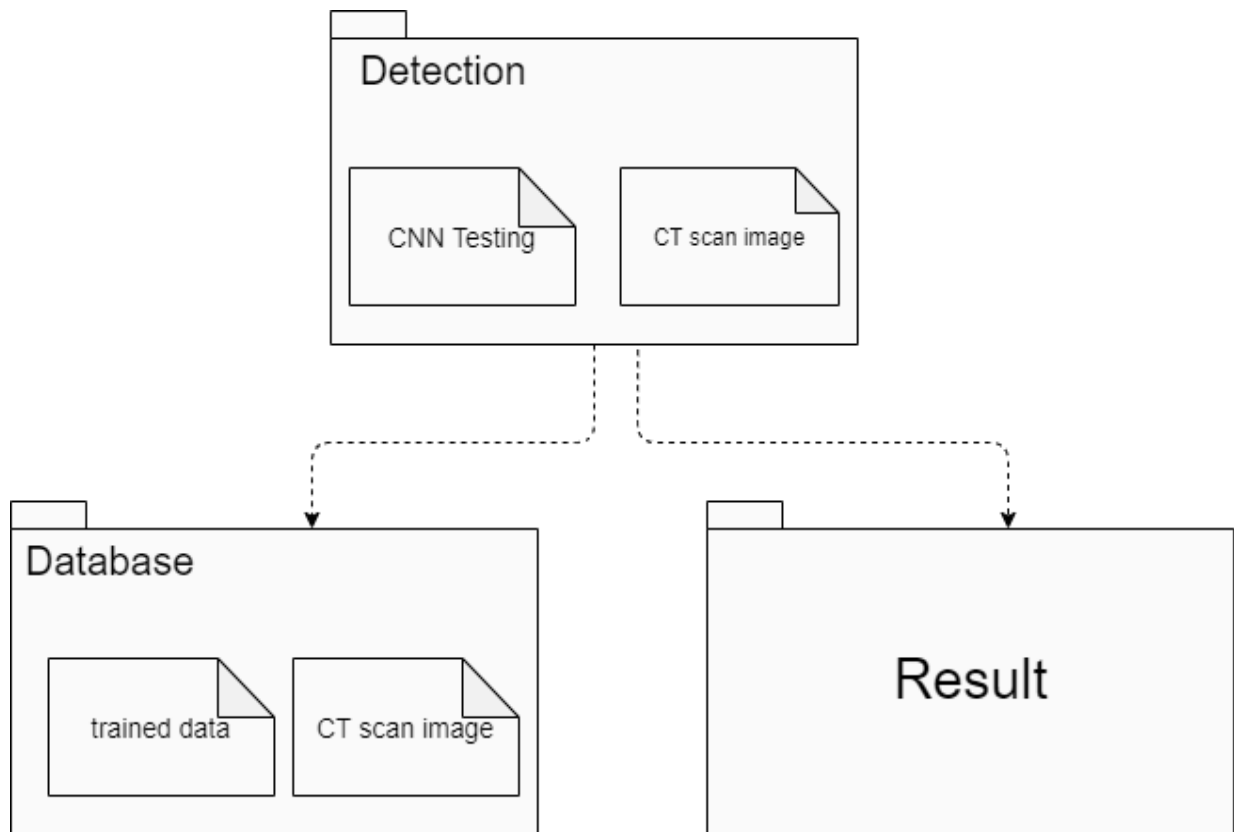


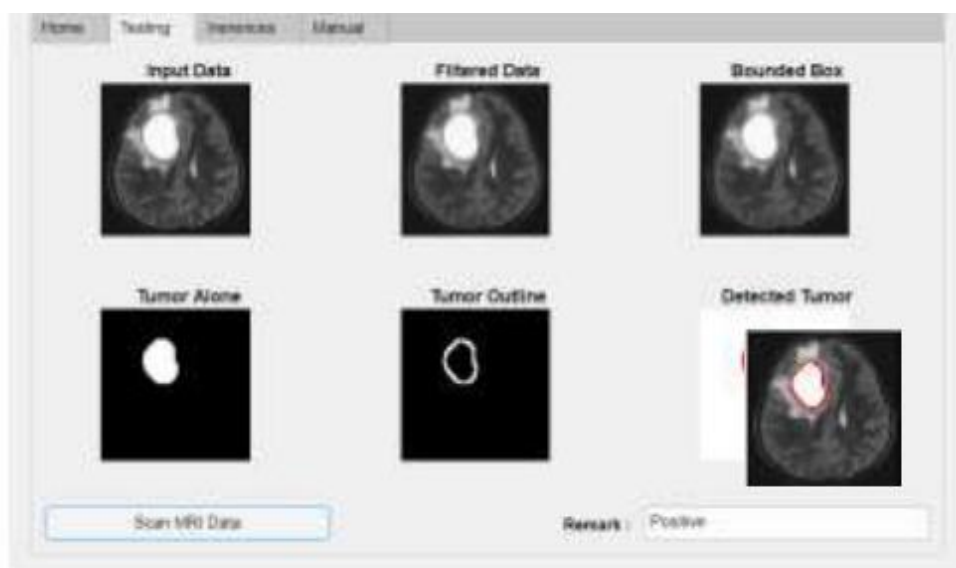
Fig.7.3.2 Package diagram of brain tumor detection system

7.4 Result

The Block chain technology is the emerging field of science, which impart a major role in every application area of science, which includes the education, Banking, and health care also. In health care most of the health issues are occur due to because of their negligence of proper diagnosis by the doctor and ignorance the symptom by patients. The most common disease now a day is called as tumor . The brain tumor is usually having a symptom like increase in headache frequently, unexplained nausea or vomiting. Sometimes it may also have blurred vision, double vision and sometimes loss of peripheral visions are also. In this project we are going to diagnose the tumor using the Blockchain strategy.

7.5 SCREEN SHOTS

For clinical feature analysis, improvement is necessary for extraction of deep layer features. For feature extraction various kinds of image enhancement methods like arithmetic operation, histogram equalization, and adaptive histogram equalization have been applied. The detection of diabetes using Iridology includes image acquisition, pre-processing, segmentation, Iris region, Normalization, Feature extraction, Classification. The results shown in fig are up to region of interest extraction for particular diagnosis using iridochart.





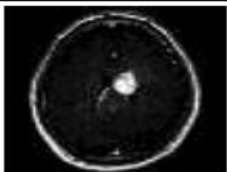
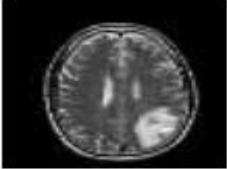
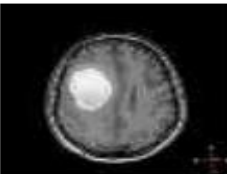
PARAMETER	STATUS	RANGE
Input Data	Available	Unavailable, Available
Filtered Data	Available	Unavailable, Available
Stranded Data	Available	Unavailable, Available
Tumor	Available	Unavailable, Available
Tumor Outline	Available	Unavailable, Available
Tumor Outline Inverted	Available	Unavailable, Available
Area	$\neq 100$	$\neq 100$, $=100$
Result	Tumor Found	Tumor Found, Tumor Not Found

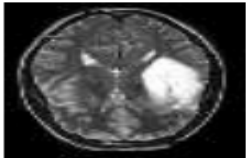
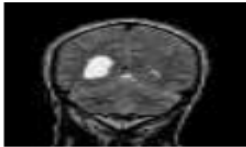
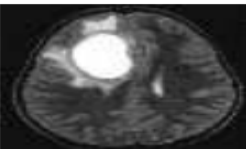
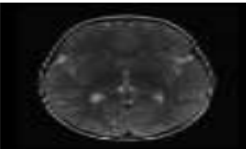
Fig. 7.5: Results in Inference Tab By analysis of results and processing time,

we can conclude that processing speed and results depend on

1. Pixel gradient
 2. Pixel size
 3. Size of image and
 4. Quality of image
- We have performed time analysis for different images and results clearly shows the dependency of time on the above-mentioned parameters.

Table 4.2 shows the processing time for different MRI Images

MRI Image in .jpg Format	Processing Time	Remarks
	175.3 milliseconds	Tumor Found
	565.5 milliseconds	Tumor Found
	202.3 milliseconds	Tumor Found

	152.1 milliseconds	Tumor Found
	168.9 milliseconds	Tumor Found
	157.1 milliseconds	Tumor Found
	733.5 milliseconds	Tumor Found Not

CHAPTER 8

ADVANTAGES, LIMITATIONS & APPLICATIONS

8.1 Advantages:

1. **Data Integrity and Security:** Blockchain provides a decentralized and tamper-proof system for storing medical data. Each transaction or record related to brain tumour detection can be securely stored in a block, and once added to the blockchain, it becomes virtually impossible to alter or delete without consensus from the network participants. This ensures the integrity and security of patient data, minimizing the risk of unauthorized access or manipulation.
2. **Privacy and Confidentiality:** With blockchain, patients can have greater control over their medical data. They can grant access to specific healthcare providers or researchers, ensuring that sensitive information related to brain tumour detection is only shared with authorized parties. Additionally, since blockchain operates on a decentralized network, there is no single point of failure, reducing the risk of data breaches and unauthorized access.
3. **Interoperability and Data Sharing:** Brain tumour detection often involves multiple healthcare providers and institutions working together. Blockchain technology enables seamless and secure sharing of relevant data among different parties. By using a common, distributed ledger, healthcare professionals can access accurate and up-to-date information, improving collaboration and decision-making in the diagnosis and treatment of brain tumours.
4. **Auditability and Traceability:** The transparent nature of blockchain allows for improved auditability and traceability of brain tumour detection processes. Each transaction or event recorded on the blockchain can be traced back to its source, providing a reliable and immutable audit trail. This can be valuable for research, quality assurance, and regulatory compliance purposes.

8.2 Limitations:

There are several limitations to this project that should be considered:

The accuracy of the diagnosis will still depend on the quality of the medical imaging results and the expertise of the medical professionals interpreting them.

1. The implementation of smart contracts will require agreement and adherence to established protocols and procedures, which may not be feasible in all medical settings.
2. The system will require access to reliable and fast internet connectivity, which may not be available in all regions.
3. The project will not address other factors that may impact patient outcomes, such as access to healthcare services, socio-economic status, and lifestyle factors
4. Cost and infrastructure requirements: Implementing blockchain technology requires significant computational resources and infrastructure. The decentralized nature of blockchain networks necessitates multiple nodes for data verification and consensus, which can be costly to maintain. Additionally, the storage capacity required to store extensive medical data, including images and reports, can be substantial, resulting in increased costs.
5. Integration with existing systems: Incorporating blockchain technology into existing healthcare systems can be challenging. Many healthcare institutions use legacy systems that may not be compatible with blockchain technology. Achieving interoperability and seamless integration between blockchain-based brain tumor detection platforms and existing systems poses technical hurdles and requires careful planning and investment.

8.3 Applications

Blockchain technology can be applied to various industries and sectors, including healthcare. While blockchain itself may not directly detect brain tumors, it can play a role in enhancing the security, privacy, and accessibility of medical data used for tumor detection and diagnosis.

1.Data Collection: Medical institutions, such as hospitals and research centres, can collect patient data related to brain tumours, including imaging scans, patient records, genetic information, and biopsy results. This data is securely stored in the blockchain, ensuring immutability and integrity.

2.Data Sharing and Collaboration: With blockchain, authorized healthcare professionals and researchers can access and share relevant patient data securely. This decentralized and transparent nature of blockchain allows for collaboration across institutions without compromising patient privacy.

3.Machine Learning and AI Integration: Machine learning algorithms and artificial intelligence (AI) can be trained using the vast amount of data stored in the blockchain. These models can help in the detection and analysis of brain tumours by analysing patterns and anomalies in medical imaging scans, genetic markers, and clinical data.

4.Second Opinions and Expert Consultations: Blockchain can facilitate the process of obtaining second opinions and expert consultations. Patients can securely share their medical data with specialists anywhere in the world, who can provide their expertise and recommendations.

5.Clinical Trials and Research: Blockchain can support the transparency and traceability of clinical trial data related to brain tumour treatments and therapies. Researchers can securely access and analyse the data, leading to advancements in diagnosis and treatment options.

6.Patient Empowerment and Ownership: Through blockchain, patients can have greater control over their medical data. They can choose to share their data for research purposes, participate in clinical trials, or seek personalized treatment options based on their unique circumstances.

CHAPTER 9

CONCLUSION

- **Conclusion:**

The prediction was successful compared to predicting test data from the same database used to train variants. However, the predictor remains poor in finding a statement associated with contempt. This may be due to a combination of lack of training and test images that clearly show contempt, poor labeling of previous data training, and internal difficulties in identifying contempt. The class divider also fails to predict the sensitivity of the test data to not only one of the seven key expressions, as they are not trained in other expressions. Future work should include improving the strength of class dividers by adding more training images from different data sets, investigating more accurate detection methods that still maintain mathematical performance, and considering classification of friendly and complex expressions for all road users. However, it is important to acknowledge that implementing blockchain technology in the field of brain tumor detection also comes with challenges. These challenges include ensuring interoperability with existing healthcare systems, addressing scalability issues, and addressing regulatory and legal considerations regarding data ownership and consent. In summary, the use of blockchain in brain tumor detection holds promise for revolutionizing the management and sharing of medical data, enhancing data integrity and security, and fostering collaboration among healthcare stakeholders. With further research, development, and collaboration between blockchain experts and medical professionals, the potential of this technology can be fully realized in improving brain tumor detection and ultimately patient care.

CHAPTER 10

FUTURE SCOPE

- **Future Scope:**

The process can be extended to a 3D image. The proper anatomical position may be detected. Fixed thresholds were used. Machine Learning may be implemented to train the system dynamically change the thresholds. A novel algorithm for the segmentation and classification of brain tumors is described in this project work. Results and analysis show that the proposed approach is a valuable diagnosing technique for physicians to detect the brain tumors. But, in the final segmentation, a few other tissues also segmented in addition to tumors.

Therefore, to improve the accuracy in the segmentation, it is necessary to include additional knowledge for discarding other tissues. In future work, it would be interesting to include additional feature information. Besides the energy, correlation, contrast and homogeneity add more information to the feature extraction to make the system more sensitive; information from the textures or location It will be interesting to continue developing more adaptive models for other types of brain tumors following the same line of work presented here. Another future line would be the detection of small malignant brain tumors. It should be clear that many factors influence the appearance of tumors on images, and although there are some common features of malignancies, there is also a great deal of variation that depends on the tissue and the tumor type. Characteristic features are more likely to be found in large tumors. Small tumors may not have many of the features of malignancy and may even manifest themselves only by secondary effects such as architectural distortion.

CHAPTER 11

BIBLIOGRAPHY

- [1]. Scott J. Social network analysis. Thousand Oaks: Sage; 2017.
- [2]. Serrat O. Social network analysis. In: Knowledge solutions. Singapore: Springer; 2017. p. 39–43
- [3]. Mikal J, Hurst S, Conway M. Investigating patient attitudes towards the use of social media data to augment depression diagnosis and treatment: a qualitative study. In: Proceedings of the fourth workshop on computational linguistics and clinical psychology—from linguistic signal to clinical reality. 2017.
- [4]. Conway M, O'Connor D. social media, big data, and mental health: current advances and ethical implications. *Curr Opin Psychol*. 2016;9:77–82.
- [5]. Ofek N, et al. Sentiment analysis in transcribed utterances. In: Pacific-Asia conference on knowledge discovery and data mining. 2015. Cham: Springer.
- [6]. Yang Y, et al. User interest and social influence based emotion prediction for individuals. In: Proceedings of the 21st ACM international conference on Multimedia. 2013. New York: ACM.
- [7]. Tausczik YR, Pennebaker JW. The psychological meaning of words: LIWC and computerized text analysis methods. *J Lang Soc Psychol*. 2010;29(1):24–54.
- [8]. Pennebaker JW, Francis ME, Booth RJ. Linguistic inquiry and word count: LIWC 2001, vol. 71. Mahway: Lawrence Erlbaum Associates; 2001. p. 2001.
- [9]. Holleran SE. The early detection of depression from social networking sites. Tucson: The University of Arizona; 2010.
- [10]. Greenberg LS. Emotion-focused therapy of depression. *Per Centered Exp Psychother*. 2017;16(1):106–17.
- [11]. Haberler G. Prosperity and depression: a theoretical analysis of cyclical movements. London: Routledge; 2017.
- [12]. Guntuku SC, et al. Detecting depression and mental illness on social media: an integrative review. *Curr Opin Behav Sci*. 2017;18:43–9.
- [13]. De Choudhury M, et al. Predicting depression via social Media. In: ICWSM, vol. 13. 2013. p. 1–10.
- [14]. De Choudhury M, Counts S, Horvitz E. Predicting postpartum changes in emotion and behavior via social media. In: Proceedings of the SIGCHI conference on human factors in computing systems. New York: ACM; 2013.
- [15]. O'Dea B, et al. Detecting suicidality on Twitter. *Internet Interv*. 2015;2(2):183–8. Signs Symptoms Behaviour Not going out any longer Not completing things at work Not doing regular

charming exercises Unfit to focus Feelings Overwhelmed Blameworthy Irritate Disappointed
Unlucky Worried Thoughts He is winner It's my pleasure Nothing good ever happens to me He
was unlucky Life is not the bed of roses He would not be able to work without me Physical
Tired Illness Headaches Depression

problem Misfortune Islam et al. Health Inf Sci Syst (2018).

- [16]. Zhang L, et al. Using linguistic features to estimate suicide probability of Chinese microblog users. In: International conference on human centered computing. Berlin: Springer; 2014.
- [17]. Aldarwish MM, Ahmad HF. Predicting depression levels using social media posts. In: 2017 IEEE 13th international Symposium on Autonomous decentralized system (ISADS). 2017. [18]. Zhou J, et al. Measuring emotion bifurcation points for individuals in social media. In: 2016 49th Hawaii international conference on system sciences (HICSS). 2016. Koloa: IEEE.
- [19]. Wang X, et al. A depression detection model based on sentiment analysis in micro-blog social network. In: Trends and applications in knowledge discovery and data mining (PAKDD). 2013.
- [20]. Nguyen T, et al. Affective and content analysis of online depression communities. IEEE Trans Affect Comput. 2014;5(3):217–26. [21]. Park M, McDonald DW, Cha M. Perception differences between the depressed and non-depressed users in Twitter. In: ICWSM, vol. 9. 2013. p. 217–226.
- [22]. Wee J, et al. The influence of depression and personality on social networking. Comput Hum Behav. 2017;74:45– 52.
- [23]. Bachrach Y, et al. Personality and patterns of Facebook usage. In: Proceedings of the 4th annual ACM web science conference. 2012. New York: ACM.
- [24]. Ortigosa A, Martín JM, Carro RM. Sentiment analysis in Facebook and its application to e-learning. Comput Hum Behav. 2014;31:527–4

**ANNEXURE I
PUBLISHED
PAPER**

Brain Tumor Detection Using Blockchain

AUTHOUR

1)Yash Zope

Department of Computer engineering
Jayavantrao Sawant college of Engineering ,Pune

AUTHOUR) 2Niraj Ohol

Department of Computer engineering
Jayavantrao Sawant college of Engineering,Pune

AUTHOUR 3) Tejas Khairnkar

Department of Computer engineering
Jayavantrao Sawant college of Engineering ,Pune

Prof. Ganga Yadawad ,Department of Computer engineering Jscoe,pune

Abstract—Brain tumor can be divided into two types: benign and malignant. Brain tumors are the most common and aggressive disease, which in its highest stage leads to a very short life expectancy. Thus, treatment planning is a key phase for improving patients' quality of life. However, it has some limitations (ie, accurate quantitative measurements are provided for a limited number of frames). A reliable and automatic classification system is therefore necessary to prevent human mortality. Blockchain technology is an emerging field of science that plays a major role in every application field of science, including education, banking, and healthcare. . In healthcare, most health problems arise due to their neglect of correct diagnosis by the doctor and ignorance of the symptom by the patients. The most common disease today is called cancer. A brain tumor usually has symptoms such as frequent headaches,unexplained nausea or vomiting. Sometimes he may also have blurred vision, double vision and sometimes loss of peripheral vision. In this project we will diagnose tumor using Blockchain strategy.

Keywords: Security, Reliability, Data Integrity, Block chain, health care, brain tumor.

I. Introduction

Brain tumor can be divided into two types: benign and malignant. Brain tumors are the most common and aggressive disease, which in the highest stage leads to a very short life expectancy. Thus, treatment planning is a key phase for improving patients' quality of life. However, it has some limitations (ie, accurate quantitative measurements are provided for a limited number of frames). Therefore, a reliable and automatic classification system is necessary to prevent human mortality. Blockchain technology is an emerging field of science that plays a major role in every application field of science, including education, banking, and healthcare. . In the healthcare industry, most health problems are caused by the doctor's neglect of the correct diagnosis and the patient's ignorance of the symptom. The most common disease today is called cancer. A brain tumor usually has symptoms such as frequent headaches, unexplained nausea or vomiting. Sometimes he may also have blurred vision,

double vision and sometimes loss of peripheral vision. In this project we will diagnose tumor using blockchain strategy

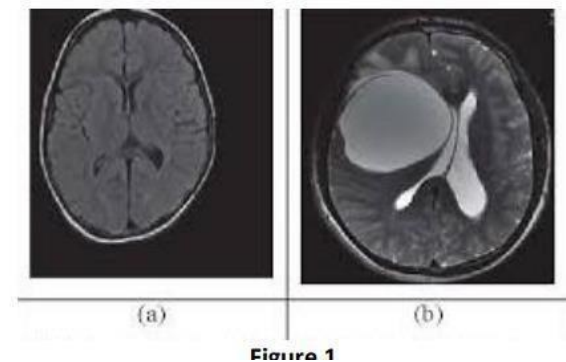


Figure-1: Example of an MRI report showing the presence of tumor in brain with solid white color mass.

Author I) Nitin Satpute ,Proposed the paper “Brain Tumour detection using Blockchain strategy”, topic of medical image processing has seen a lot of diverse work done recently. The topic of medical image processing is now home to scientists from a variety of disciplines, such as computer vision and machine learning. Consequently, we examined some of the studies conducted to determine the most efficient and advanced techniques that might be significant for us. Devkota et al. [1] developed the complete segmentation process on the basis of Mathematical Morphological Operations and the spatial FCM technique, which decreases computational effort, although the suggested solution has not been tested to the assessment stage. It identifies malignancy with 92% accuracy and labels it with 86.6% accuracy. In the study by Dr. Chinta Someswararao [2] , where he used a combined Convolution neural network classifier model for determining whether or not the patient has a brain tumor along with machine vision to automatically crop the patient's brain from MRI scans. His overall accuracy is much higher than, say, the criterion of 50%. However, it might be significantly enhanced by using more train data or alternative models and approaches. By combining a clever edge detection technique with adaptive thresholding, Badran et

al. [3] were able to extract the ROI. The dataset contained 102 images. A Canny algorithm for edge detection and adaptive thresholding were applied to the initial and next following set of the neural network respectively after the images had been preprocessed. The removal of Brain Tumors was made simple, fully automated, and effective by Khurram Shahzad and Imran Siddique [4]. The use of morphological gradients and thresholds, as well as morphological operations like erosion and dilation, is made. The morphological gradient is used to calculate the threshold. When the image is converted to black and white using threshold, a tumor and some noise appear on the screen. By compressing the image and employing erosion techniques to reduce noise or unwanted little elements, the image is thinned. Following erosion, dilation is used to rebuild the portion of the removed tumor that erosion has destroyed.

Author II) C. Sowmiya, Dr.P. Sumitra proposed "Brain Tumour detection using Blockchain strategy" to excel in a variety of machine vision-based systems, Muhammed Talo et al. [5] designed AlexNet, a CNN architecture. A dearth of datasets that are pre-tagged is one of the main factors holding back the progress of deep learning techniques in the medical sector. In order to enhance general accuracy, a data augmentation strategy was used that addresses this by increasing the quantity of data points from easily accessible annotated picture data sources. The performance of transfer learning models derived from convolutional neural networks was good when weight sharing generated a network large enough to conduct computerized malignancy detection or prediction using Computed tomography data. Ravikumar Guruswamy and Dr. Vijayan Subramaniam [7] reprocessed and retrieved the MRI image characteristics in study. This study made use of both real-time and simulated visuals. Next, to eliminate the undesired disturbances, an intensive preprocessing procedure is used.

According to Author III) Aditya Gupta, presents a novel approach for noise removal, retrieval, and malignancy identification on MRI images. This stage has a significant success rate, which ensures the system's overall reliability. For segmentation and pattern maintenance, Joseph et al. [8] used Lloyd's algorithm (k-means) and Support vector machine algorithms, and they built a relationship between Support Vector Machine and the skull masking strategy. A mix of Lloyd's segmentation and Support Vector Machine technique with skull masking is used to produce a better result. They altered the feature extraction method as well as the previously used Lloyd's k-means approach to conceal more of the cranial tissue and generate a more accurate tumor-detecting scan. As a result, identifying the type of tumor, its location, and the stage, which has yet to be precisely identified, might allow us to achieve far more.

According to Author IV) Venkatesh Iotlikar, the major purpose of their work is to separate malignant cells from the BRATS 2018 dataset and use variables such as age, contours, and volumetric factors to predict overall patient survival rate. They also tackled the difficulty of identifying brain cancer types and estimating survival rates, for which they employed several ways and determined the accuracy of each method so that they might modify that method. The proposed method utilizes fewer

features but achieves more accuracy than state-of-the-art approaches.

Author V) Dr. Manoj S. and Yuvaraju B, the mortality prognosis into three categories based on factors such as age and tumor type: short-term, medium-term, and long-term survivors. Several research papers on brain tumor classification and detection have been published, some of the researchers employed traditional classifiers, while others utilized deep learning techniques. Some works that employed traditional methods to achieve a significant result, while others did not. However, we may deduce from these results that deep learning outperforms traditional classifiers owing to its learning process and network memory consumption.

A. Problem Definition:

The primary goal of this work is to create a model that can predict whether or not MRI images include cancer. We created and trained a model that could detect the tumor, presenting an efficient and effective way for assisting in the segmentation and identification of brain tumors that eliminates the need for manual labor. Finally, when we compared the outcomes of all tests, we discovered that certain models performed better in terms of accuracy and loss metrics.

Proposed Methodology:

In this study, to improve the performance and reduce the complexity involved in the CT scan image. Brain tumors can be detected manually by experts from the CT scan images we apply Preprocessing on that and show the accurate result

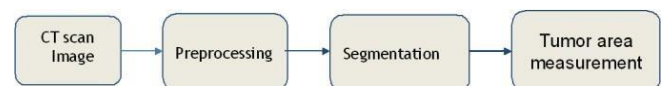


Fig 1. Methodology of Brain Tumor Detection

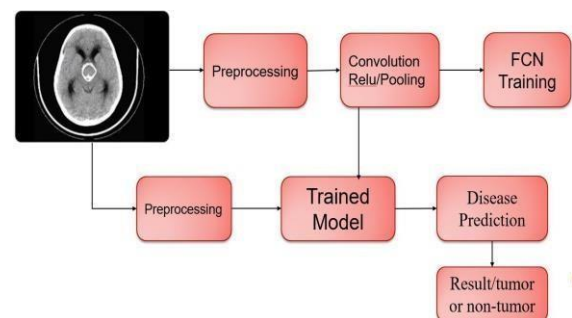


Fig 2 Architecture of Brain Tumor Detection system

□ CT SCAN IMAGE:

The term "computed tomography", or CT, refers to a computerized x-ray imaging procedure in which a narrow beam of x-rays is aimed at a patient and quickly rotated around the body, producing signals that are processed by the machine's computer to generate cross-sectional images or

“slices” of the body. These slices are called tomographic images and contain more detailed information than conventional x-rays. Once a number of successive slices are collected by the machine’s computer, they can be digitally “stacked” together to form a three-dimensional image of the patient that allows for easier identification and location of basic structures as well as possible tumors or abnormalities.

□ Preprocessing

Successful Segmentation of the image is followed by the post-processing of the image. Pre- Processing of the image involves steps to judge the size of the tumor and its type. Pre-processing may also involve various optimization techniques to further improve the result.

Preprocessing is consist of three steps:

Gray-level

conversion.Resizing of image.Median

filtering.

□ Segmentation:

The process of splitting an image into multiple parts is known as segmentation. It creates various sets of pixels within the same image. Segmenting an image makes it easier for us to further analyze and extract meaningful information from it. It is also described as “The process of labeling each pixel in an image such that they share the same characteristics”. The process results in pixels sharing a common property.

□ Tumor Area Measurement:

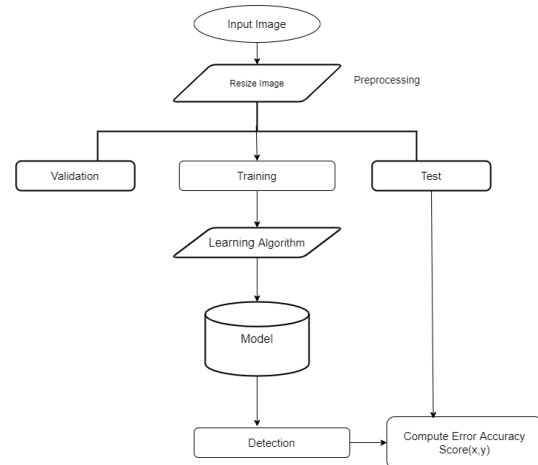
Two CT scans from each of 31 patients were collected. Using a computer interface, five observers contoured tumor on three selected CT sections from each baseline scan. Four observers also constructed matched follow-up scan tumor contours for the same 31 patients. Area measurements extracted from these contours were compared using a random effects analysis of variance model to assess relative inter observer variability. The sums of section area measurements were also analyzed, since these area sums are more clinically relevant for response assessment

Block chain

The diagnosis of brain tumors is usually based on imaging data analysis of brain tumor images. Accurate analysis of brain tumor images is a key step in determining a patient's condition. Therefore, how to accurately detect brain tumor images is very important. Brain MRI image is mainly used to detect the tumor and tumor progress modeling process. This information is mainly used for tumor detection and treatment processes. MRI image gives more information about given medical image than the CT or ultrasound image.

MRI image provides detailed information about brain structure and anomaly detection in brain tissue. Actually, Scholars offered unlike automated methods for brain tumors finding and type cataloging using brain MRI images from the time when it became possible to scan and freight medical images to the computer. Conversely, Neural Networks (NN)

and Support Vector Machine (SVM) are the usually used methods for their good enactment over the most recent few years. So we propose a system where we use MRI or CT scan images as input and using Machine Learning and Block chaining we will detect brain tumor of the patient. CNN (Convolutional Neural Networks) Algorithm will be used to train our model and block chaining will play an important role for transferring data using particular block



II. Advantages

The doctor identify the disease earlier and improve patient outcomes drastically. Today, advanced Medical Imaging offers numerous benefits to both the healthcare providers and the patients. CNN is the best approach for medical image processing to find accurate and quick result. Following some advantages of our system is helpful for:

1. Better Diagnosis
 2. Complicated Surgeries
 3. Affordable Health Care Costs
 4. Safe & effective
 5. File-sharing Ecosystem & Data Privacy
- High Accuracy.
 - Less efficient.

Applications

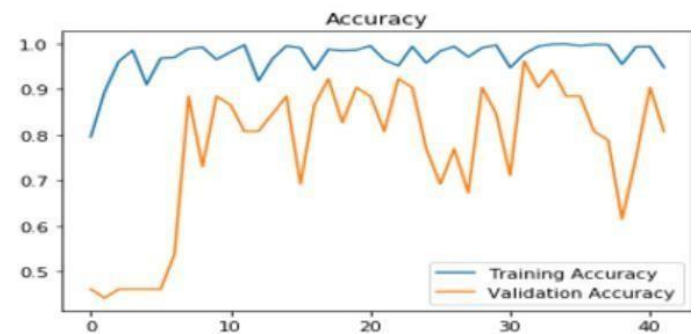
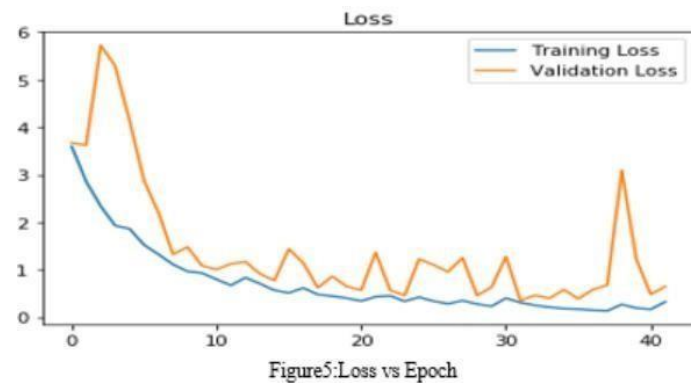
- Leaf Disease Detection.
- Medical image processin

iii. Conclusion

The main goal of this research work is to design efficient automatic brain tumor classification with high accuracy, performance and low complexity. This project consists of the details about the model which was used for the detection of brain tumor using the MRI images of the brain from the normal persons and the persons who had a brain tumor. If it is deployed in the real-time scenario then it will help many people in diagnosing the brain tumor without wasting the money on check-up. If the brain tumor is confirmed by the model, then the person can reach the nearest hospital to get the treatment. It can be the best way of practice for people to save money. As we know that the data plays a crucial role in every deep learning model, if the data is more specific and accurate about the symptoms of the brain tumor then that can help in reaching greater accuracy with better results in real-time applications..

The Database was gathered from Kaggle, named 'Brain MRI Images for brain tumor Detection' By NavoneelChakrabarty.[6] The dataset comprises 253 Brain MRI Images in the folders yes and no. The folder yes contains 155 timorousbrain MRI images, whereas the folder now has 98 non-timorous brain MRI images.

Experiments were conducted on 2065 photos, 1085 of which had malignancies and 980 of which did not. The dataset is further split as: 70% as training, 10% as validation, and 20% as testing; each experiment was conducted for up to 50 epochs with early stopping to control overfitting. On the 32nd epoch, the model had a test accuracy of 89% and a test loss of 0.3033, learning rate is 0.001.



Algorithm	Accuracy	loss	Epoch	Batch size	Learning Rate
-----------	----------	------	-------	------------	---------------

Referen

- [1] Nowak R D, Wavelet-based radian noise removal for magnetic resonance imaging. IEEE Trans Image Processing 1999; 8(10):1408- 1419.
- [2] White D, Houston A, Sampson W, Wilkins G. Intra and inter-operator variations in region-of- interest drawing and their effect on the measurement of glomerular filtration rates 1999; 24:177–81
- [3] UDUPA, J. K., LEBLANC, V. R., ZHUGE, Y., IMIELINSKA, C., SCHMIDT, H., CURRIE, L. M., "A framework for evaluating image segmentation algorithms," Computerized Medical Imaging and Graphics, 30:75-87, 2006.
- [4] Zhuang AH, Valentino DJ, Toga AW. Skull stripping magnetic resonance brain images using a model-based level set. Neuro Image 2006;32(1):79-92.
- [5] Angelini E D, Clatz O, Mandonnet E, Konukoglu E, Capelle L, Duffau H. Gli-oma dynamics and computational models: a review of segmentation, registration, and in silico growth algorithms and their clinical applications. Curr. Med. Imaging 2007; 3: 262–76

- [6] Rajesh Dass, Priyanka, Swapna Devi, "Image Segmentation Techniques", IJECT Vol.3, Issue 1, Jan-March 2012.
- [7] Bauer S, Wiest R, Nolte L, Reyes M. A survey of MRI-based medical image analysis for brain tumor studies. *Phys Med Biol*.2013;58:97129
- [8] Gordillo N, Montseny E, Sobrevilla P. State of the art survey on MRI brain tumor segmentation. *Magn Reson Imaging* 2013; 31(8):1426–38
- [9] Savita Agrawal and Deepak Kumar Xaxa, "Survey on Image Segmentation Techniques and Color Models," *International Journal of Computer Science and Information Technologies (IJCSIT)*, Vol. 5 (3), 3025-3030, 2014
- [10] D. Kwon et al. Combining generative models for multifocal glioma segmentation and registration. *Medical Image Computing and Computer-Assisted Intervention–MICCAI 2014*. Springer, 2014:763–770.
- [11] Liu J, Wang J, Wu F, Liu T, Pan Y. A survey of MRI-based brain tumor segmentation methods. *Tsinghua Science and Technology* 2014;19(6):578-595.
- [12] Urban G. et al. Multi-modal brain tumor segmentation using deep convolutional neural networks. *MICCAI Multimodal Brain Tumor Segmentation Challenge (BraTS)* 2014:31–35.
- [13] Zikic D. et al. Segmentation of brain tumor tissues with convolutional neural networks. *MICCAI Multimodal Brain Tumor Segmentation Challenge (BraTS)* 2014:36–39.
- [14] Davy A. et al. Brain tumor segmentation with deep neural networks. *MICCAI Multimodal Brain Tumor Segmentation Challenge (BraTS)* 2014:1–5.
- [15] Riddhi.S.Kapse, Dr. S.S. Salankar, Madhuri.Babar "Literature Survey on Detection of Brain Tumor from MRI Images" *IOSR Journal of Electronics and Communication Engineering (IOSR-JECE)* e-ISSN: 2278- 2834, p-ISSN: 2278-8735. Volume 10, Issue 1, Ver. II (Jan - Feb. 2015), PP 80-86
- [16] A.Sindhu, S.Meera "A Survey on Detecting Brain Tumor in MRI Images Using Image Processing Techniques" *International Journal of Innovative Research in Computer and Communication Engineering* Vol. 3, Issue 1, January 2015
- [17] Menze B, et al. The Multimodal brain tumor image segmentation benchmark (brats). *IEEE Trans Med Imaging* 2015; 34(10):1993- 2024.
- Rao V, Sarabi M S, Jaiswal A. Brain tumor segmentation with deep learning. *MICCAI Multimodal Brain Tumor Segmentation Challenge (BraTS)* 2015:56–59.
- [18] Anitha and S. Murugavalli, "Brain tumor classification using two-tier classifier with adaptive segmentation technique," *IET Computer Vision*, 2016, vol. 10(1), pp. 9-17.
- [17] Havaei M, Davy A, Farley W D, Biard A, Courville A, Bengio Y, Pal C, Jodoin PM, Larochelle H. Brain tumor segmentation with deep neural networks. *Medical Image Analysis* 2016, DOI:10.1016/j.media.2016.05.004.

ANNEXURE II CERTIFICATES



JSPM'S
JAYAWANTRAO SAWANT COLLEGE OF ENGINEERING
Department of Computer Engineering



CERTIFICATE OF PARTICIPATION

This is to certify that

Yash zoze

has participated in the Project Competition held in
Computer Department, JSCOE on 13th May, 2023

PROF. N. R. ZINZURKE
PROF. S. S. WAGH
Project Coordinator

Dr. P.D. LAMBHATE
HOD (Computer Dept.)

Dr. R.D. KANPHADE
Principal, JSCOE



JSPM'S
JAYAWANTRAO SAWANT COLLEGE OF ENGINEERING
Department of Computer Engineering



CERTIFICATE OF PARTICIPATION

This is to certify that

Niraj ohol

has participated in the Project Competition held in
Computer Department, JSCOE on 13th May, 2023

PROF. N. R. ZINZURKE
PROF. S. S. WAGH
Project Coordinator

Dr. P.D. LAMBHATE
HOD (Computer Dept.)

Dr. R.D. KANPHADE
Principal, JSCOE



JSPM'S
JAYAWANTRAO SAWANT COLLEGE OF ENGINEERING
Department of Computer Engineering



CERTIFICATE OF PARTICIPATION

This is to certify that

Tejas Khairnar

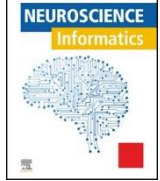
has participated in the Project Competition held in
Computer Department, JSCOE on 13th May, 2023

PROF. N. R. ZINZURKE
PROF. S. S. WAGH
Project Coordinator

Dr. P.D. LAMBHATE
HOD (Computer Dept.)

Dr. R.D. KANPHADE
Principal, JSCOE

ANNEXURE III BASE PAPERS



Artificial Intelligence in Brain Informatics

MRI-based brain tumour image detection using CNN based deep learning method



Arkapravo Chattopadhyay*, Mausumi Maitra

Department of Information Technology, Government College of Engineering and Ceramic Technology, Kolkata-700010, West Bengal, India

article info

Article history:

Received 25 November 2021

Received in revised form 19 February 2022

Accepted 21 February 2022

abstract

Introduction: In modern days, checking the huge number of MRI (magnetic resonance imaging) images and finding a brain tumour manually by a human is a very tedious and inaccurate task. It can affect the proper medical treatment of the patient. Again, it can be a hugely time-consuming task as it involves a huge number of image datasets. There is a good similarity between normal tissue and brain tumour cells in appearance, so segmentation of tumour regions become a difficult task to do. So there is an essentiality for a highly accurate automatic tumour detection method.

Method: In this paper, we proposed an algorithm to segment brain tumours from 2D Magnetic Resonance brain Images (MRI) by a convolutional neural network which is followed by traditional classifiers and deep learning methods. We have taken various MRI images with diverse Tumour sizes, locations, shapes, and different image intensities to train the model well. Furthermore, we have applied SVM classifier and other activation algorithms (softmax, RMSProp, sigmoid, etc) to cross-check our work. We implement our proposed method using “TensorFlow” and “Keras” in “Python” as it is an efficient programming language to perform fast work.

Result: In our work, CNN gained an accuracy of 99.74%, which is better than the state of the result obtained so far.

Conclusion: Our CNN based model will help the doctors to detect brain tumours in MRI images accurately, so that the speed in treatment will increase a lot.

© 2022 The Author(s). Published by Elsevier Masson SAS. This is an open access article under the CC BY-NC-ND license (<http://creativecommons.org/licenses/by-nc-nd/4.0/>).

1. Introduction

Medical imaging refers to several techniques that can be used as non-invasive methods of looking inside the body [1]. The main use of medical image in the human body is for treatment and diagnostic purposes. So, it plays a significant role in the betterment of treatment and the health of the human.

Image segmentation is a crucial and essential step in image processing that determines the success of image processing at a higher level [2]. In this case we have mainly focused on the segmentation of the brain tumour from the MRI images. It helps the medical representatives to find the location of the tumour in the brain easily. Medical image processing encompasses the utilization and exploration of 3D image datasets of the physical

body, obtained most typically from computed tomography (CT) or Magnetic Resonance Imaging

(MRI) scanner to diagnose pathologies or guide medical interventions like surgical planning, or for re-

* Corresponding author.

E-mail addresses: arkapravo1998@gmail.com (A. Chattopadhyay), mou1232005@yahoo.com (M. Maitra).

search purposes. Medical image processing is applied by radiologists, engineers, and clinicians to understand the anatomy of either individual patients or population groups highly. Measurement, statistical analysis, and creation of simulation models which incorporate real anatomical geometries provide the chance for more complete understanding, as an example of interactions between patient anatomy and medical devices.

Tumour: The word “Tumour” is a synonym for the word “neoplasm” which is formed by an abnormal growth of cells. A tumour is significantly different

from cancer [3].

1.1. Classification of tumour

There are three basic types of tumours: 1) Benign; 2) PreMalignant; 3) Malignant (cancer can only be malignant) [4].

1.1.1. Benign tumour

A Benign Tumour is not always Malignant or cancerous. It might not invade close tissue or unfold to alternative components of the body the

<https://doi.org/10.1016/j.neuri.2022.100060>

2772-5286/© 2022 The Author(s). Published by Elsevier Masson SAS. This is an open access article under the CC BY-NC-ND license (<http://creativecommons.org/licenses/by-nc-nd/4.0/>).

way cancer can. In most cases, the outlook with benign tumours is not at all serious but it can be serious if it presses on vital structures such as blood vessels or nerves.

1.1.2. Pre-Malignant tumour

In these tumours, the cells are not cancerous. However, they need the potential to become malignant. The cells will grow and unfold to alternative components of the body.

1.1.3. Malignant tumour

Malignancy (mal- = “bad” and ignis = “fire”) Malignant tumours area are cancerous. They develop once cells grow uncontrollably. If the cells still grow and unfold, the malady will become dangerous. Malignant tumours will grow quickly and unfold to alternative components of the body during a method known as metastasis.

A latest research [5] in the year 2021 says that in United States among 24530 adults (13840 men & 10690 Women) will be identified with cancerous tumours of brain and in the spinal cord. A person’s probability of developing this type of brain tumour in their lifespan is less than 1%. It causes 85% to 90% of all primary central nervous system (CNS) tumours. A number of 3,460 children under the age of 15 will also be identified with a brain or CNS tumour this year, other than this deals with adult primary brain tumours. Brain and alternative system nervous cancer is the tenth leading reason behind death for men and women. It is evaluated that 18,600 adults (10,500 men & 8,100 women) may die from primary cancerous brain and CNS tumours in the year 2021. Hence it’s important to improve the accuracy of previously proposed methods for the betterment of medical image research. In our paper, our proposed 99.74%

Brain tumor Detection using Blockchain accurate CNN-based algorithm will help medical representatives in their treatment job without manually analyzing the MRI images so that the treatment speed can be enhanced.

2. Methods for

Brain Tumour segmentation methods can be divided as three parts. Manual methods, Semi-automatic methods and Absolute automatic methods. We can determine it according to the level of user interaction required [6].

2.1. Manual segmentation methods

It needs a medical specialist to use the different information picturize by the MRI images along with anatomical and physiological knowledge achieve through training and experience. This procedure requires the medical specialist going through multiple slices of images part by part, analyzing the brain Tumour and manually cropping the tumour regions carefully. It’s a time consuming task as manual segmentation is also doctor dependent and segmentation results are subject to large intra and inter ratter variability [7]. Although, this is widely applied to execute the results of semi-automatic and fully automatic techniques.

2.2. Semi-automatic segmentation methods

It needs the reaction of the user for three main purposes; initialization, intervention or feedback response and evaluation [8]. Initialization is mainly executed by defining a region of interest (ROI), restraining the estimated Tumour area, for the automatic algorithm to process. Parameters of pre-processing technique can also be balanced to fit the input images. In addition to initialization, automated algorithms can be directed towards a necessary result throughout the procedure by receiving feedbacks. This process also provides the adjustments in response. Again, user can estimate the results and change or repeat the procedure again if not satisfied. Hamamci et al. proposed the “Tumour Cut” method [9]. This method comprised applying the algorithm separately to each MRI modality (e.g. T1, T2, T1-Gd and FLAIR). Then we combine the outcome to obtain the final tumour volume. A current semi-automatic method applied to a novel classification approach [10]. In this technique segmentation problem was converted

into a classification problem and a brain tumour is segmented by training and classifying within that same brain only. Commonly, a machine learning classification technique, for brain tumour segmentation, needs a large quantity of brain MRI scans images (with checked answers) from different cases to train. This outcome in a necessity handles intensity bias correction and other noises. Although in this approach, user initializes the procedure by sort out a subset of voxels linked with each tissue type, from a single case. For these subsets of voxels, algorithm extracts the intensity values along with spatial coordinates as features and trains a support vector machine (SVM) that is used to classify all the voxels of the same image to their corresponding tissue type. Semi-automatic brain tumour segmentation approach not only takes reduces time than manual method but also it can maintain efficient results but still prone to intra and inter-rater user variability. Therefore, recent brain tumour segmentation research is mainly focused on fully automatic methods.

2.3. Absolute automatic segmentation methods

In this approach user does not need any interaction. Most importantly, artificial intelligence and preparatory knowledge are merged to solve the segmentation problem.

2.3.1. Challenges

Automatic segmentation of gliomas (A type of tumour that occurs in the brain and spinal cord) is a very tuff and important problem. Brain tumour MRI data obtained from clinical scans or synthetic databases [11] are naturally complicated. The devices for MRI and protocols that are using for acquisition can vary significantly from scan to scan imposing intensity biases and other variations for each different part of image in the dataset. Several modalities need to significantly segment tumour sub-regions even adds to this complexity.

2.3.2. BRATS dataset

BRATS refer to “The Multimodal Brain Tumour Image Segmentation Benchmark”. Objective assessment of the outcome of different brain tumour image segmentation approaches with the state-of-the-art is a difficult task. Moreover with the implement of a widely accepted benchmark, the BRATS benchmark [12], for automatic brain tumour segmentation, now it’s reality to objectively comparison various glioma segmentation

Brain tumor Detection using Blockchain approaches using this common dataset. Latest version (2020) of the BRATS training dataset has 369 multi-modality MRI scans, out of which 293 have been acquired from glioblastoma (GBM/HGG) and 76 from lower grade glioma (LGG) of patients with gliomas (both high and low grades) along with their ground truth segmentations for assessment [13]. Assessment on the testing data is only possible with the online assessment tool. Outcomes are represented by the tool mainly in the form of popularly known Dice Score, Sensitivity (true positive rate) and Specificity (true negative rate) for three main tumour parts; whole tumour (all tumour components), core tumour (all tumour components except edema) and active tumour (only active cells). Dice scores are mainly used for performance measures. For each tumour region, P1 represents the segmented tumour area by the proposed method, and T1 is the actual tumour area in the ground truth. Then, dice score is calculated by the online tool for each region as

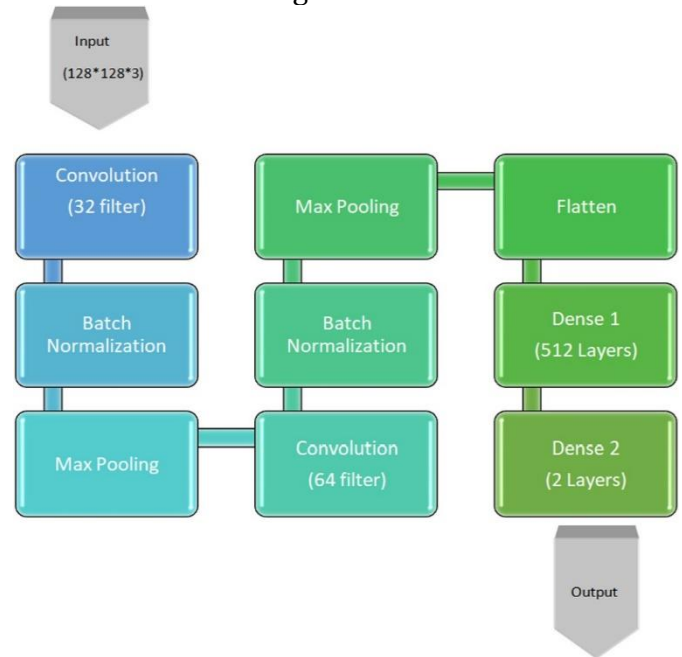


Fig. 1. Proposed methodology for tumour detection using 9-Layer Convolutional Neural Network.

$$= \frac{|P1 \cap T1|}{(|P1| + |T1|)/2} \quad |P1 \cap T1| \text{ Dice}(P, T)$$

3. Proposed methodology

Convolutional Neural Network is a well-ordered technique in the field of the medical image process. A convolutional neural network (CNN) could be a type of artificial neural network works in image recognition and process that’s specifically designed for method component knowledge. CNN is a powerful image processing, computing method that

use deep learning to perform each generative and descriptive tasks, typically exploitation machine vision that has image and video recognition, together with recommender systems and linguistic communication process (NLP). A neural network could be a combination of system of hardware and computer code similar to the operation of neurons within the human brain. Artificial neural networks are not ideal for the image process. A CNN uses a system very like a multilayer view-point that has been designed for reduced process necessities. The removal of limitations and increase in potency for image process ends up in a system which is way more effective, easier to train data for image process and linguistic communication process. We have changed the fundamental CNN model and projected a far better version of it. In our 9 layer CNN model, there are fourteen stages, as well as the hidden layers, which provide us with the foremost outstanding result for the apprehension of the tumour. The diagram presented in Fig. 1 is the projected methodology with a short narration.

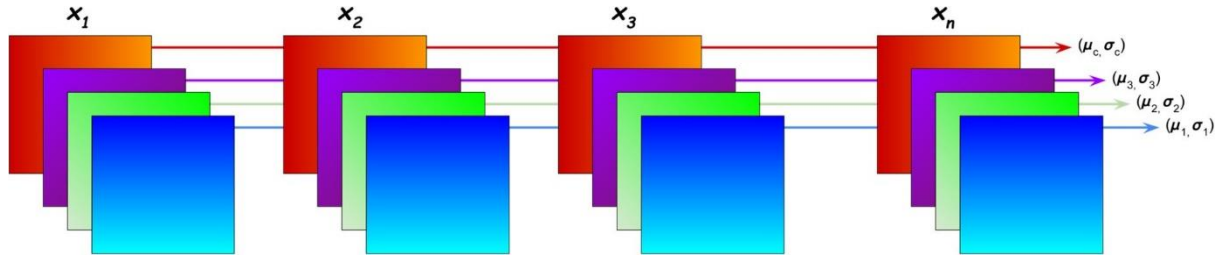


Fig. 2. Batch normalization.

scaling. We used it to form our algorithm quicker. See Fig. 2.

Next, the pooling operation implies sliding a 2D filter over each channel of the feature map and summarizing the features lying within the region covered by the filter. The dimensions of output obtained after a pooling layer for a feature map with dimensions $n_h * n_w * n_c$ is

$$(n_h - f + 1) / s * (n_w - f + 1) / s * n_c$$

where,

- > n_h - height of feature map
- > n_w - width of feature map
- > n_c - no. of channels in the feature map
- > f - size of filter
- > s - stride length

A normal CNN model architecture is to have many convolutional and pooling layers piled up one after the other.

Pooling layers are used to decrease the dimensions

of the feature maps. Thus, it decreases the number of parameters to learn the amount of computation performed in the network. The pooling layer summarise the features present in a range of the feature map generated by a convolutional layer. Therefore, further operations are performed on summarize features instead of accurately positioned features created by the convolutional layer. This makes the model more powerful to dissimilar in the position of the features in the input image. Here, we have used a 2*2 Max pooling operation [16] that selects the maximum element from the range of the feature map covered by the filter. So, the output after the max-pooling layer would be a feature map containing the most important features of the previous feature map. See Fig. 3. After this stage, we again used 64 filter convolutional, batch normalization, max-pooling methods before doing the flattening. We proposed two dense layers where the first dense layer has 512 hidden layers and 2nd dense layer has the final 2 layers. In the final layer, we used softmax as an

activation function, as it is giving more accuracy than others. Again we used “categorical_crossentropy” as loss function and RMSProp (Root Mean Squared Propagation, or RMSProp, is an extension of gradient descent and Adaptive

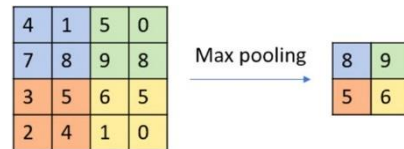


Fig. 3. 2*2 Maxpooling operation.

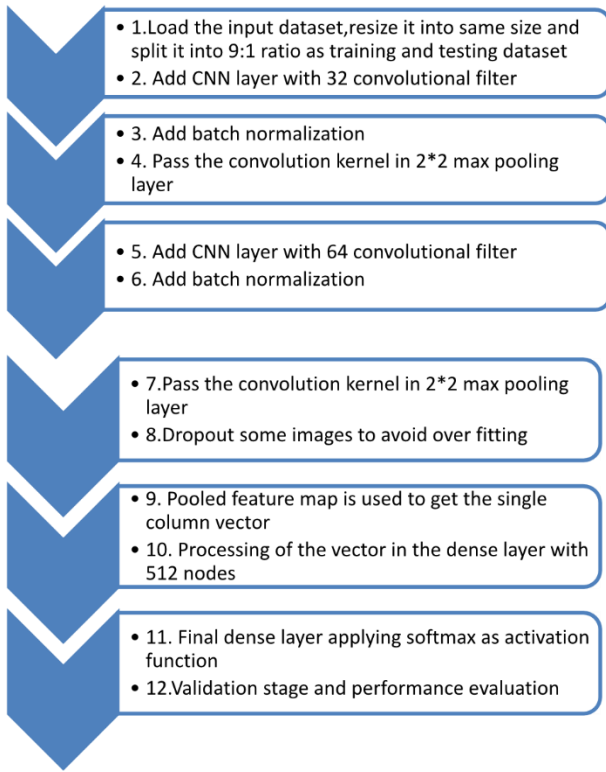


Fig. 4. Working flow of the proposed CNN model.

Gradient Algorithm version of gradient descent that uses a decaying average of partial gradients in the adaptation of the step size

Table 1

Comparison of different models.

Final Layer Activation Method	Optimizer	Accuracy (%)	Testing Accuracy (%)	Evaluation of the Model (%)
SVM	N/A	15.17	20.83	24.17
Sigmoid	RMSProp	97.63	58.33	68.72
Softmax	AdaMax	98.10	75	82.40
Softmax	RMSProp	99.74	93.78	97.71

Brain tumor Detection using Blockchain for each parameter.) as optimizer. Fig. 4 shows the working flow of the proposed CNN model. **4.**

Experimental results

4.1. Experimental dataset

We used the 2020 BraTS dataset for our experiment. We took a total of 2892 images with different types of tumours like T1, T2, and FLAIR. This dataset is consisting of two classes, where class 1 refers to tumour images and class 0 refers to non-tumour images. Some tumour datasets and non tumour dataset from our input images are shown in Fig. 5 and 6 respectively.

4.2. Results and discussion

Table 1 and Table 2 show our experimental results with different models, activation functions, optimizers of CNN. First we tried AdaMax (AdaMax algorithm is an extension to the Adaptive Movement Estimation (Adam) Optimization algorithm. More broadly, is an extension to the Gradient Descent Optimization algorithm) as optimizer then we found the accuracy of 99.74% using softmax in the final layer and RMSProp as optimizer, which is obtained for using 2473 number of training images, 273 number of testing images with 9:1 splitting ratio. Here we dropped out some images (around 5%) from the total 2892 image dataset to prevent over fitting.

Final output of the proposed method using 11 numbers of epoch has been shown in Fig. 7. Fig. 8 shows the training and validation accuracy with respect to the number of epochs and the corresponding loss is shown in Fig. 9.

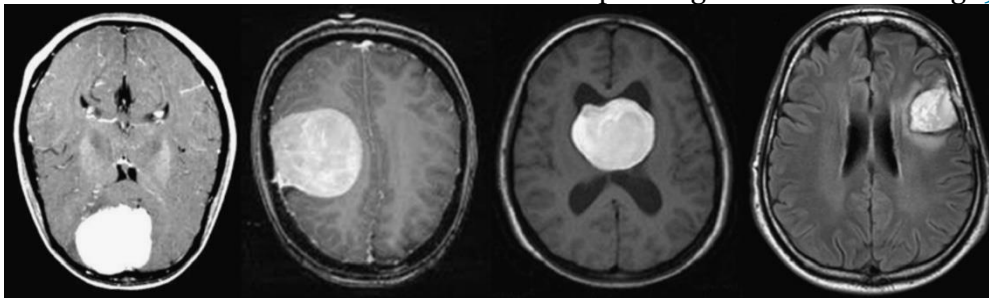


Fig. 5. Images with tumours.

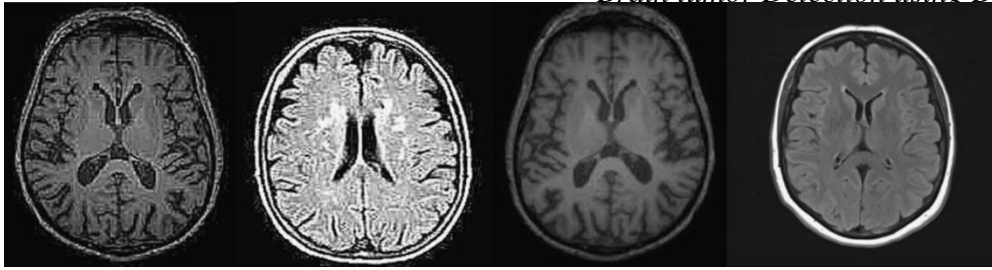


Fig. 6. Images with non-tumours.

```

... Epoch 1/11
58/58 [=====] - 80s 1s/step - loss: 13.7427 - accuracy: 0.7406 - val_loss: 1.8259 - val_accuracy: 0.6839
Epoch 2/11
58/58 [=====] - 79s 1s/step - loss: 0.6205 - accuracy: 0.8180 - val_loss: 0.8964 - val_accuracy: 0.8256
Epoch 3/11
58/58 [=====] - 79s 1s/step - loss: 0.2587 - accuracy: 0.9105 - val_loss: 1.3833 - val_accuracy: 0.8670
Epoch 4/11
58/58 [=====] - 79s 1s/step - loss: 0.1062 - accuracy: 0.9680 - val_loss: 0.7154 - val_accuracy: 0.8929
Epoch 5/11
58/58 [=====] - 79s 1s/step - loss: 0.1095 - accuracy: 0.9715 - val_loss: 0.1962 - val_accuracy: 0.9413
Epoch 6/11
58/58 [=====] - 79s 1s/step - loss: 0.0536 - accuracy: 0.9849 - val_loss: 1.6301 - val_accuracy: 0.8549
Epoch 7/11
58/58 [=====] - 79s 1s/step - loss: 0.0442 - accuracy: 0.9909 - val_loss: 0.5464 - val_accuracy: 0.9016
Epoch 8/11
58/58 [=====] - 79s 1s/step - loss: 0.0688 - accuracy: 0.9862 - val_loss: 0.1340 - val_accuracy: 0.9706
Epoch 9/11
58/58 [=====] - 82s 1s/step - loss: 0.0257 - accuracy: 0.9927 - val_loss: 0.4262 - val_accuracy: 0.9499
Epoch 10/11
58/58 [=====] - 81s 1s/step - loss: 0.0072 - accuracy: 0.9974 - val_loss: 0.2805 - val_accuracy: 0.9706
Epoch 11/11
58/58 [=====] - 75s 1s/step - loss: 0.0128 - accuracy: 0.9974 - val_loss: 0.4951 - val_accuracy: 0.9378

```

Fig. 7. Final output of our proposed method.

Table 2

Performance of the proposed CNN model.

No	Training Image	Testing Image	Splitting Ratio	Accuracy (%)
1	2199	543	8:2	99.73
2	2473	273	9:1	99.74

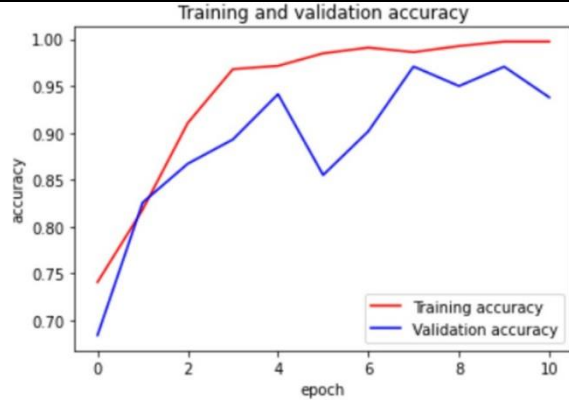


Fig. 8. Training and validation accuracy.

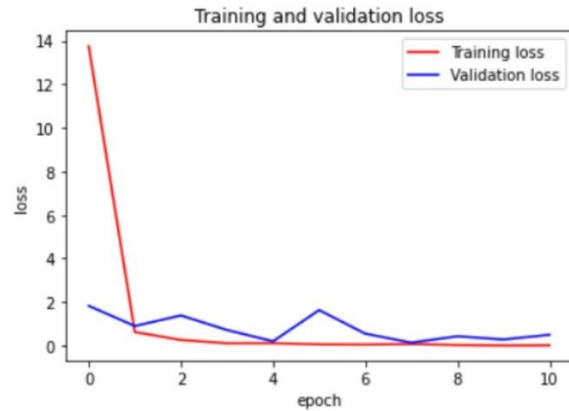


Fig. 9. Training and validation loss.

In this proposed model we got 99.74% accuracy that is higher than the state of the art results obtained by Seetha et al. [17] and Tonmoy Hossain et al. [18] as mentioned in the Table 3. An example of predicted output image has been shown in Fig. 10.

Table 3

Performance comparison.

Methodology	Accuracy (%)
Seetha et al. [17]	97.50
Tonmoy Hossain et al. [18]	97.87
Proposed CNN model	99.74

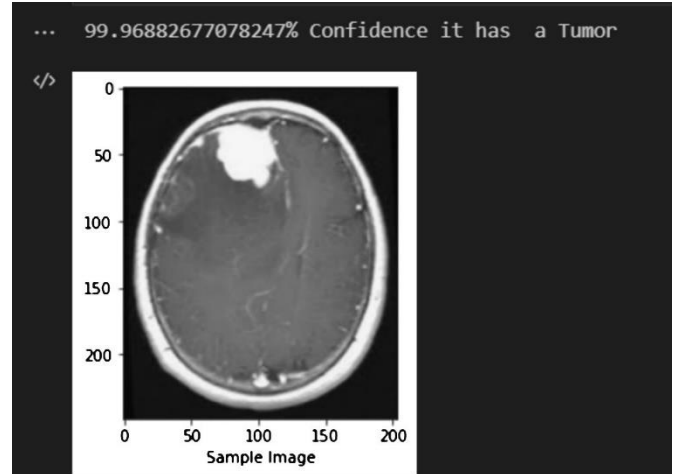


Fig. 10. Prediction by our proposed model.

5. Conclusion

MRI is most vastly used for tumour segmentation and classification. Although, convolutional neural networks (CNN) have the advantage of automatically learning representative complex features for both healthy brain tissues and tumour tissues directly from the multi-modal MRI images, so we decided to improve its accuracy. First we tried to implement SVM on CNN, but we got low accuracy of only 20.83%. Then we tried different parameters. We changed the final layer parameter to softmax and optimizer to AdaMax. Then we got 98.10% accuracy. But we need more, so we decided to change the optimizer to RMSProp, and finally we got the output accuracy to 99.74%. By using 2473 numbers of image as training data and 273 images for testing in 9:1 ratio with 11 epoch procedure we ultimately got our final result. Our model has 9 layer CNN model with 14 stages. Most importantly we also deleted some images to overcome overfitting.

Declaration of competing interest

We declare that we have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgements

We acknowledge West Bengal Higher Education Department, Govt. of West Bengal for providing necessary fund through the Swami Vivekananda Merit cum Means (SVMCM) Scholarship for M.Tech to Arkapravo Chattopadhyay (Application ID WB32101602736839).

References

Hany Kasban, Mohsen El-bendary, Dina Salama, A comparative study of medical imaging techniques, *Int. J. Inf. Sci. Intell. Syst.* 4 (2015) 37–58; J. Clerk Maxwell, *A Treatise on Electricity and Magnetism*, vol. 2, 3rd ed., Clarendon, Oxford, 1892, pp. 68–73.

D. Surya Prabha, J. Satheesh Kumar, Performance evaluation of image segmentation using objective methods, *Indian J. Sci. Technol.* 9 (8) (February 2016).

Anam Mustaqeem, Ali Javed, Tehseen Fatima, *Int. J. Image Graph. Signal Process.* 10 (2012) 34–39.

M.L. Oelze, J.F. Zachary, W.D. O'Brien Jr., Differentiation of tumour types in vivo by scatterer property estimates and parametric images using ultrasound backscatter, vol. 1, 5-8 Oct. 2003, pp. 1014–1017.

Brain Tumour: Statistics, Cancer.Net Editorial Board, 1/2021. (Accessed on January 2021).

N. Gordillo, E. Montseny, P. Sobrevilla, State of the art survey on MRI brain tumour segmentation, *Magn. Reson. Imaging* 31 (8) (2013) 1426–1438.

D. White, A. Houston, W. Sampson, G. Wilkins, Intra and interoperator variations in region-of-interest drawing and their effect on the measurement of glomerular filtration rates, *Clin. Nucl. Med.* 24 (1999) 177–181.

J.L. Foo, A survey of user interaction and automation in medical image segmentation methods, Tech rep ISUHCI20062, Human Computer Interaction Department, Iowa State Univ., 2006.

A. Hamamci, et al., Tumour-Cut: segmentation of brain Tumours on contrast enhanced MR images for radiosurgery applications, *IEEE Trans. Med. Imaging* 31 (3) (2012) 790–804.

M. Havaei, H. Larochelle, P. Poulin, P.M. Jodoin, Within-brain classification for brain tumour segmentation, *Int. J. Cars* 11 (2016) 777–788.

M. Prastawa, E. Bullitt, G. Gerig, Simulation of brain tumours in MR images for evaluation of segmentation efficacy, *Med. Image Anal.* 13 (2) (2009) 297–311.

Yixin Wang, et al., Modality-pairing learning for brain tumour segmentation, arXiv:2010.09277v2 [eess.IV], 29 Dec 2020.

W. Zhang, Y. Wu, B. Yang, S. Hu, L. Wu, S. Dhelim, Overview of multi-modal brain tumour MR image segmentation, *Healthcare* 9 (2021) 1051, <https://doi.org/10.3390/healthcare9081051>.

Sergey Ioffe, Christian Szegedy, Batch Normalization: Accelerating Deep Network Training by Reducing Internal Covariate Shift.

<https://learnopencv.com/batch-normalization-in-deep-networks/>.

Giorgos Tolias, Ronan Sifre, Hervé Jégou, Particular object retrieval with integral max-pooling of CNN activations, arXiv:1511.05879 [cs.CV], 2015.

J. Seetha, S. Selvakumar Raja, Brain tumour classification using convolutional neural networks, *Biomed. Pharmacol. J.* 11 (2018) 1457–1461, <https://doi.org/10.13005/bpj/1511>.

Tonmoy Hossain, Fairuz Shadmani Shishir, Mohsena Ashraf, M.D. Abdullah Al Nasim, Faisal Muhammad Shah, Brain tumour detection using convolutional neural network, in: 1st International Conference on Advances in Science, Engineering and Robotics Technology, ICASERT, 3-5 May 2019, 2019.