



BRAIN TUMOR DETECTION USING DEEP LEARNING

¹ Prof. S.P. Pingat, ¹Sakshi Deshmukh, ¹Sampana Bhosale, ¹Pratiksha Deshmukh, ¹Safiya Inamdar

Department Of Computer Engineering,

Smt. Kashibai Navale College of Engineering, Pune, India.

Abstract: This work deals with the implementation of Simple Algorithm for detection of range and shape of tumor in brain MR images and identifies stage of tumor from the given area of tumor. Tumor is an uncontrolled growth of tissues in any part of the body. Tumors are of different types and they have different Characteristics and different treatment. As it is known, brain tumor is inherently serious and life- threatening because of its character in the limited space of the intracranial cavity (space formed inside the skull). Most Research in developed countries show that the number of people who have brain tumors weredied due to the fact of inaccurate detection. Generally, CT scan or MRI that is directed into intracranial cavity produces a complete image of brain.After researching a lot statistical analysis which is based on those people whose are affected in brain tumor some general Risk factors and Symptoms have been discovered. The development of technology in science day night tries to develop new methods of treatment. This image is visually examined by the physician for detection & diagnosis of brain tumor. However this method accurate determines the accurate of stage & size of tumor and identifies stage of tumor from the area of tumor. This work uses segmentation of brain tumor based on the k-means algorithms.This method allows the segmentation of tumor tissue with accuracy and reproducibility comparable to manual segmentation. In addition, it also reduces the time for analysis and identifies stageof tumor from the given area of tumor.Finally implement a system using java to identify stage of tumor which is easier, cost reducible and time savable.

Index Terms – Brain Tumor Detection, Deep Learning.

I.INTRODUCTION

The field of healthcare diagnostics has transformed in recent years with the incorporation of deep learning techniques in medical image analysis. The detection and classification of brain tumors, which continue to be highly challenging because of the complexity and diversity of tumor features, is one of the crucial areas benefiting from recent improvements. Deep learning has demonstrated encouraging results in increasing the precision and effectiveness of brain tumor diagnosis complex. An overview of the use of deep learning techniques for brain tumor identification from medical imaging data is provided in this work, with an emphasis on magnetic resonance imaging (MRI) scans.Brain tumor detection using deep learning involves training neural networks to analyze medical imaging data, such as MRI or CT scans, to identify the presence and characteristics of tumors in the brain. This process typically involves several steps: preprocessing of the images, feature extraction, model training, and evaluation.Deep learning models, such as convolutional neural networks (CNNs), are often employed due to their ability to automatically learn relevant features from the data. These models are trained on labeled datasets containing images of both healthy brains and brains with tumors, allowing them to learn to differentiate between the two. Once trained, the models can be used to classify new images and assist radiologists in diagnosing brain tumors more accurately and efficiently. Online In this work, two algorithms are used for segmentation. K-means clustering algorithm and CNN algorithm. So it gives the accurate result for tumor segmentation. Tumor is due to the uncontrolled growth of the tissues in any part of the body. The tumor may be primary or secondary.If it is an origin, then it is known as primary. If the part of the tumor is spread to another place andgrown as its own then it is known

as secondary. Normally brain tumor affects CSF (Cerebral Spinal Fluid). It causes for strokes. The physician gives the treatment for the strokes rather than the treatment for tumor. So detection of tumor is important for that treatment. The lifetime of the person who affected by the brain tumor will increase if it is detected

at current stage. That will increase the lifetime about 1 to 2 years. Normally tumor cells are of two types. They are Mass and Malignant. The detection of the malignant tumor is somewhat difficult to mass tumor. In this paper we focused on detection of brain tumor with the help of Brain MRI images and identify stage of tumor from the given area of tumor. In the field of medical imaging, brain tumor detection is a crucial endeavor that could save a patient's life. Convolutional Neural Networks (CNN), a subset of deep learning, have become a potent technique for automating the identification of brain cancers from diagnostic imaging like MRI and CT scans. With the use of this technology, tumor diagnosis could become much more accurate and efficient, allowing for earlier intervention and better patient outcomes. Benign or malignant growths within the brain can be called brain tumors. Traditionally, radiologists have used medical image analysis to detect and diagnose malignant cancers. This is a labor-intensive and human error-prone technique. Artificial intelligence (AI) component deep learning has revolutionized medical image processing, particularly the diagnosis of brain tumors. In order to effectively treat brain cancers, early discovery is essential. The application of deep learning algorithms, such as CNNs, has the potential to reduce the need for invasive operations and save lives by enabling faster and more accurate detection. It can also help medical professionals by offering a screening tool or second opinion to validate or reinforce their first diagnosis. Convolutional neural networks, or CNNs, are a subclass of deep learning models created especially for the processing of images. They are made up of several layers of pooling and convolutional algorithms that use the input images to create hierarchical representations. Internet Two algorithms are employed for segmentation in this paper. CNN algorithm and the K-means clustering algorithm. As a result, the tumor segmentation result is correct. Any section of the body's tissues that grow out of control might develop tumors. There could be a primary or secondary tumor. It is referred to as primary if it is an origin. A tumor is classified as secondary if a portion of it has developed and spread to a different location. Cerebral spinal fluid, or CSF, is typically affected by brain tumors. Strokes are caused by it. Treatment for strokes is administered by the doctor instead of treatment for tumors. Therefore, tumor diagnosis is crucial to the course of treatment. The lifespan of the brain-affected individual

II. LITERATURE SURVEY

To comprehend the present state of research and advancements in the field of digital grievance handling, one must first understand the literature survey for the online complaint management system. This survey explores a wide range of topics related to complaint handling, user involvement, and technology solutions through a thorough analysis of academic publications, research articles, and real-world implementations. It looks at how complaint management systems have changed over time in both the public and private spheres, highlighting the benefits and problems of using digital technology to expedite the complaint resolution process. The survey evaluates the effects of online interfaces, mobile applications, and geographic information systems (GIS) on improving user experiences and raising grievance handling efficiency. Additionally, it looks into administrative responsibilities, user feedback systems, and the usage. The literature survey for the online complaint management system is an important basis for understanding the current level of research and advancements in the field of digital grievance management. This assessment delves into a wealth of scholarly studies, research articles, and practical applications that cover a wide range of complaint management, user engagement, and technology solutions. It looks at the evolution of complaint management systems in both the public and commercial sectors, giving light on the obstacles and opportunities that come with expediting the complaint resolution process through digital methods. The poll also evaluates how mobile applications, online interfaces, and geographic information systems (GIS) improve user experiences and increase grievance handling efficiency. Additionally, it looks into user feedback systems, administrative roles, and the usage

III. METHODOLOGY

The proposed system has mainly four modules: preprocessing, segmentation, Feature extraction, approximate reasoning and classification. Pre-processing is done by filtering. Segmentation is carried out by advanced K-means and CNN algorithms. Feature extraction is by thresholding and finally, Approximate reasoning method to recognize the tumor area and position in MRI image and identify stage of tumor from result area of brain tumor. I.e. finally implement a system to identify stage of tumor which is easier, cost reducible and time savable. The proposed method is a combination of two algorithms.

Advantages:

1. It consist two algorithms for clustering and classification which effectively able to extract tumor from image and gives the actual final result.
2. This proposed system effectively able to extract all the spatial characteristics of an Image.

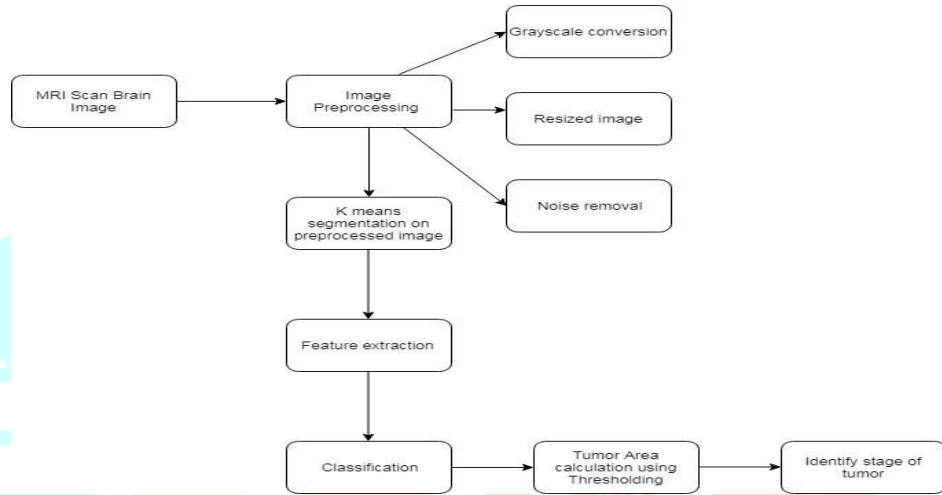


Fig. 1 System Architecture

This sequence diagram depicts the process flow for detecting brain tumors using deep learning. It starts with user registration/login, then uploads brain MRI and skull images. The system then processes these images using techniques such as K-Means clustering and Convolutional Neural Networks (CNN) to detect tumor regions and stages, yielding a disease risk prediction.

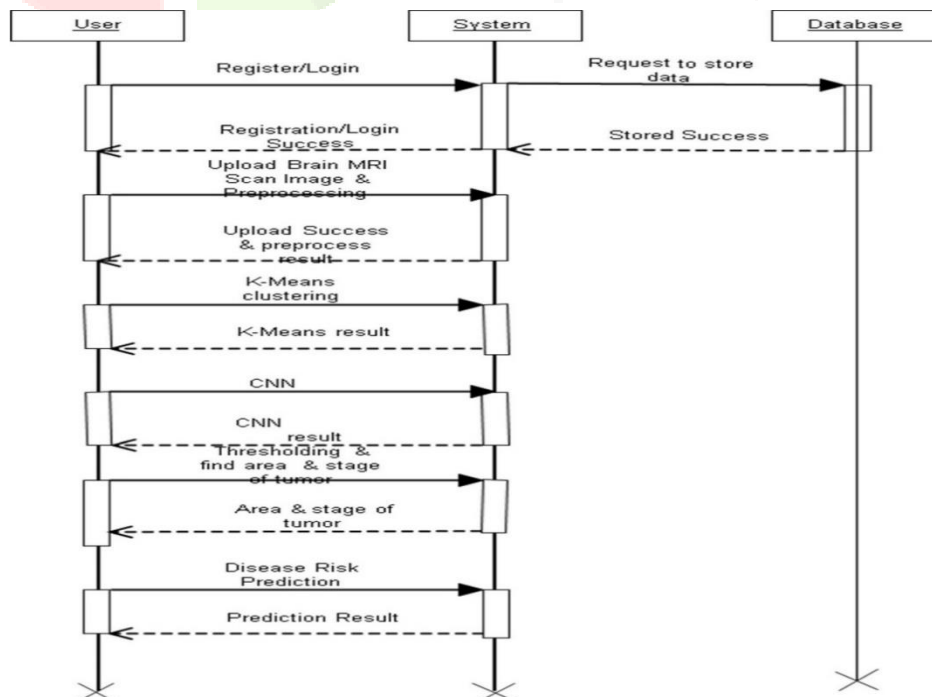


Fig . 2 Sequence Diagram

The Waterfall Model is sequential design process, often used in Software development processes; where progress is seen as flowing steadily down through the phase of conception, Initiation, Analysis, Design, Construction, Testing, Production/Implementation and Maintenance.

There are 5 Phase of water fall model

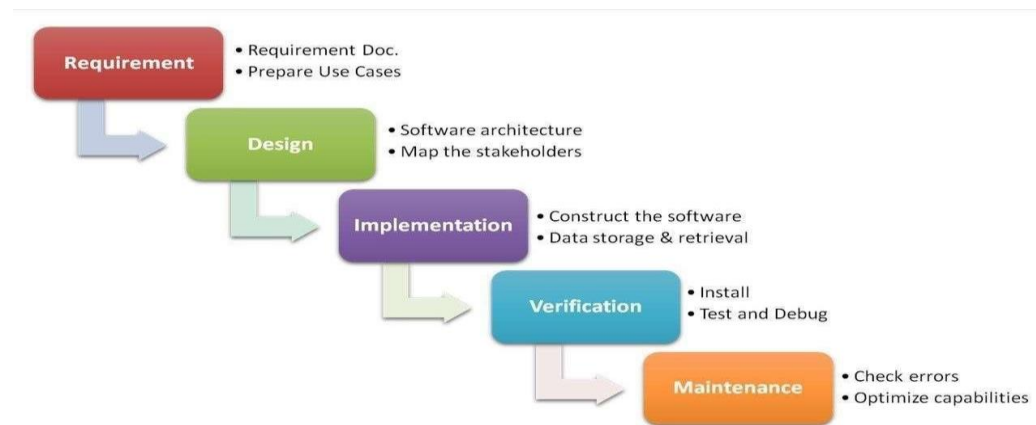


Fig.3 SDLC Model

Requirement Gathering and analysis: Here requirements are gathered means which kind of dataset we have to use. Then what are functional requirement of system. Document is prepared that use cases are designed.

Implementation: In this stage system is developed according to module wise: Admin module and user module.

Verification: This stage all developed software are installed and they are tested with different way against system requirements.

Maintenance: According to software's new version and there use them need to update. In our system some browser are not supportive to our web pages for that we need to use only specific browser.

IV. PROPOSED ALGORITHM

ALGORITHM 1

CNN Algorithm

The structure of CNN algorithm includes mainly three layers

1) Convolutional Layer

This layer is the first layer that is used to extract the various features from the input images

In this layer the mathematical operation of convolution is performed between the input image and a filter of a particular size $M \times M$

2) Pooling layer

The primary aim of this layer is to decrease the size of the convolved feature map to reduce the computational cost

Pooling layer are used to reduce the spatial dimensions of the feature maps.

3) Fully connected layer

- In this, the input image from the previous layers are flattened and fed to the FC layer.
- In this stage, the classification process begins to take place.
- Goal of this layer is to make class prediction.

ALGORITHM 2

K-Means Algorithm

Deep learning for brain tumor detection does not typically employ the K-means algorithm directly. Instead, convolutional neural networks (CNNs) or other designs that are well-suited for picture classification. K-means clustering, however, can occasionally be utilized for feature extraction or as a preprocessing step. K-means clustering, for instance, can be used to group together comparable image patches or to lower the dimensionality of the input data before supplying it to a deep learning model. This can enhance the deep learning model's efficacy and efficiency, particularly when handling high-dimensional data like medical images. Convolutional layers for feature extraction and pooling layers to lower dimensionality and boost computing efficiency are two

prominent architectures for deep learning models used to detect brain tumors. For categorization, fully connected layers usually come after these.

IV. FUTURE SCOPE

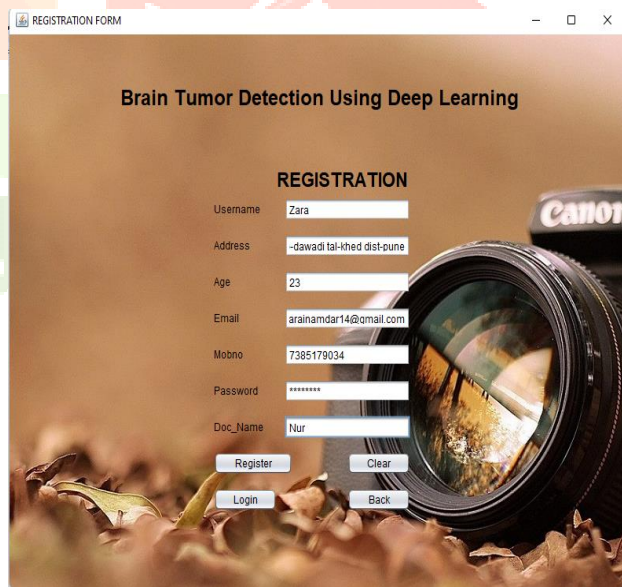
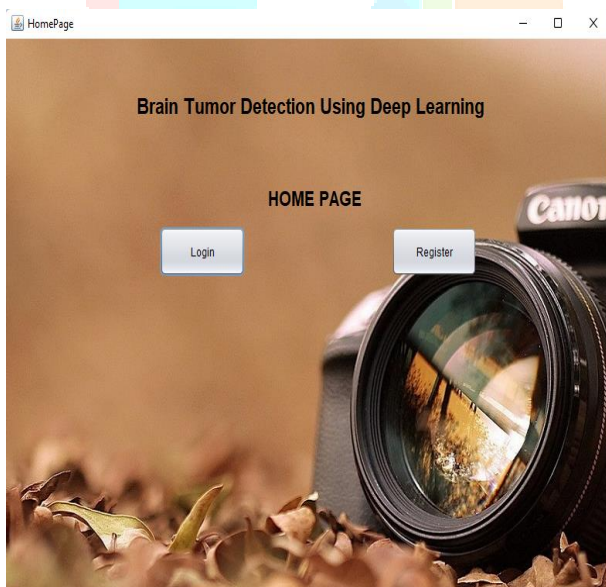
1. In future we will enhance this system to implement an android application and also on 3D images.
2. In future We will find types of brain tumor.

VI. SYSTEM IMPLEMENTATION

Module-ID:-01

Modules to be tested:-Registration

1. Enter the case insensitive Username click on Submit button.
Expected: It should display error.
2. Enter the case sensitive Username click on Submit button.
Expected: It should accept.
3. Enter the case insensitive Password click on Submit button.
Expected: It should display error.
4. Enter the case sensitive Password click on Submit button.
Expected: It should accept.
5. Enter the case insensitive Mobile Number click on Submit button.
Expected: It should display error.
6. Enter the case sensitive Mobile Number click on Submit button.
Expected: It should accept.
7. Enter the wrong address and click on Submit button.
Expected: It should display error.
8. Enter the correct address and click on Submit button.
Expected: It should accept.



Module-ID:-2

Modules to be tested:- Login

1. Enter the correct username and wrong password click on Submit button.

Expected: It should display error.

2. Enter the wrong username and correct password and click on Submit button.

Expected: It should display error.

3. Enter the correct username and password and click on Login button.

Expected: It should display welcome page.

4. After login with valid credentials click on back button.

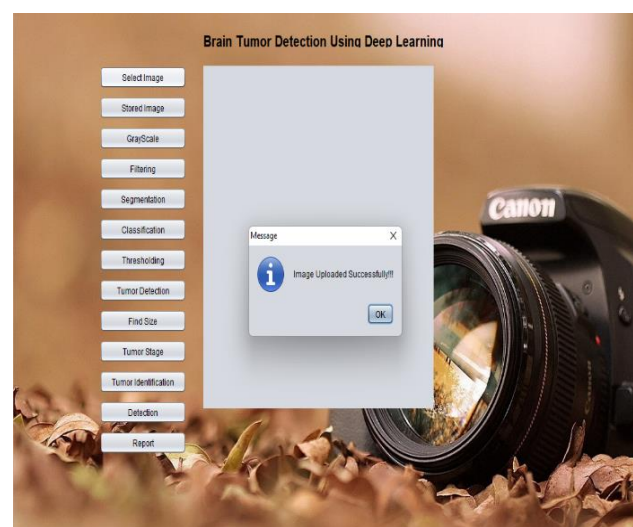
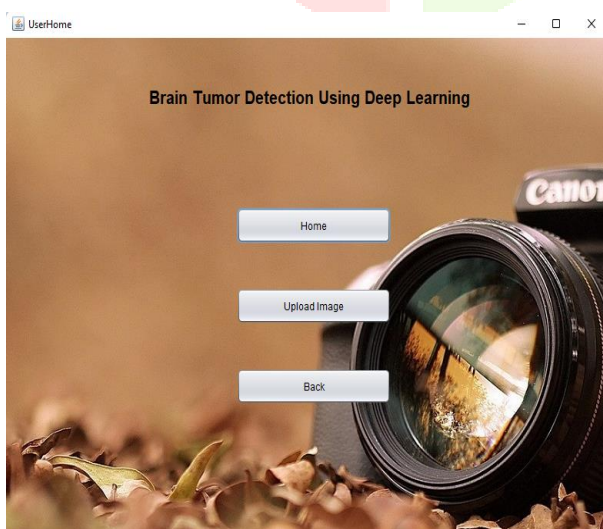
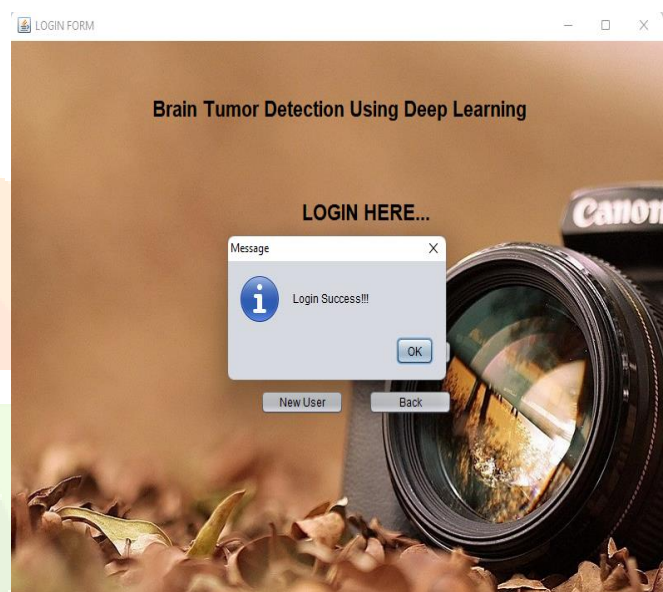
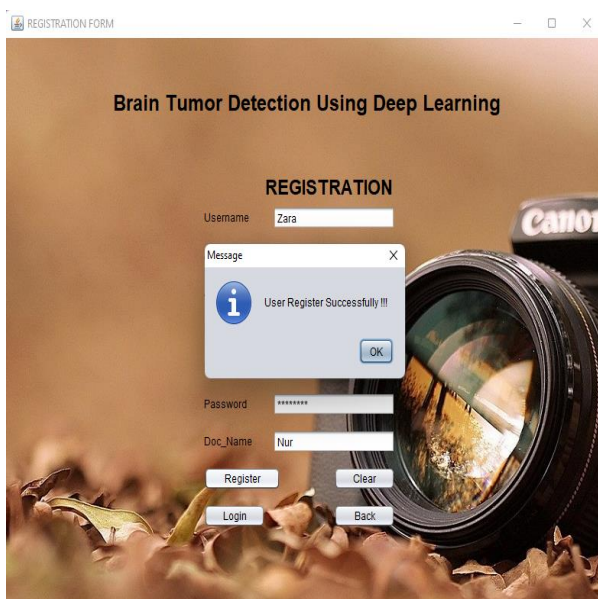
Expected: The page should be expired.

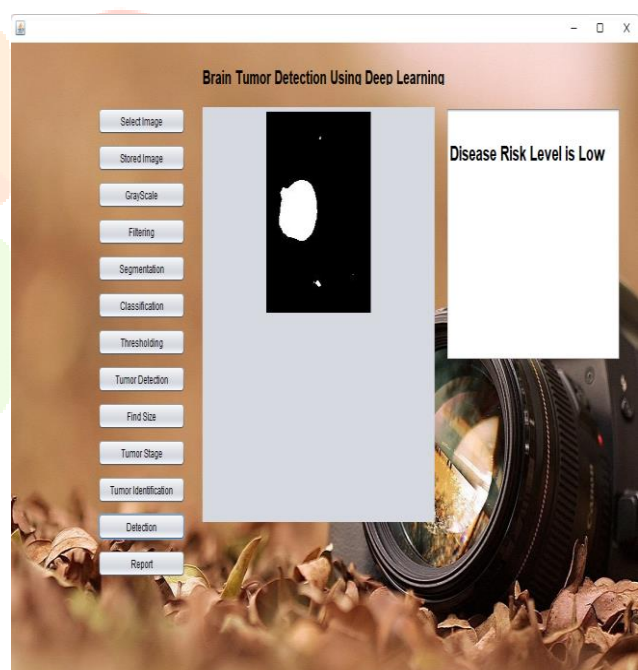
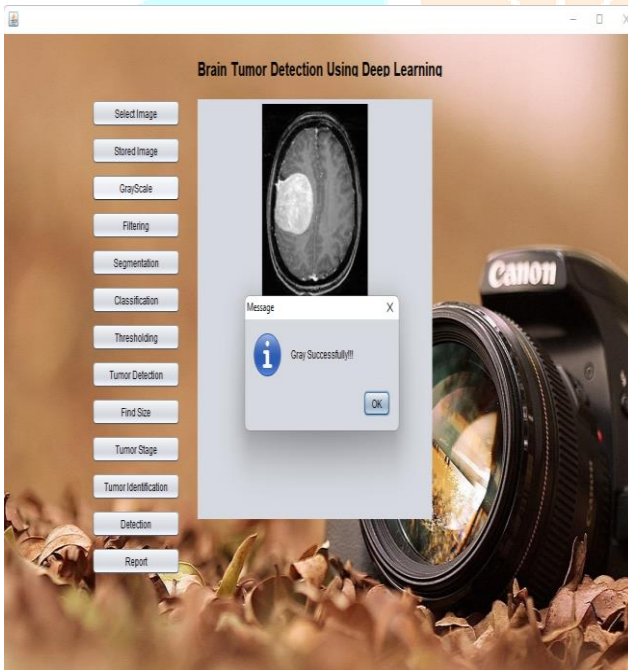
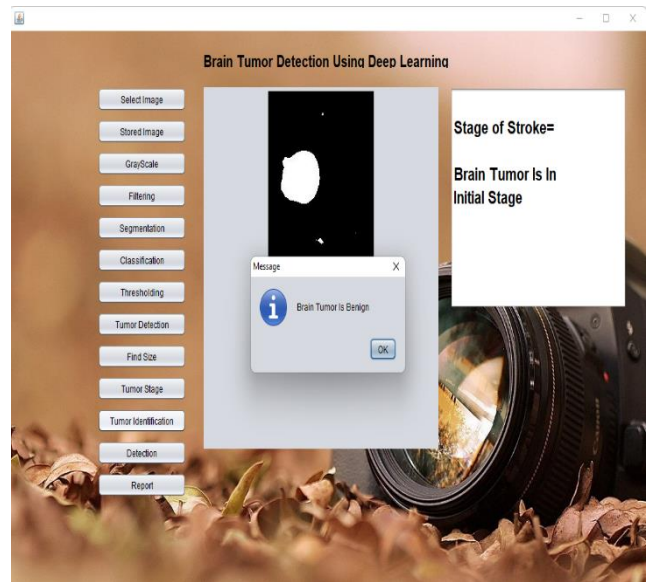
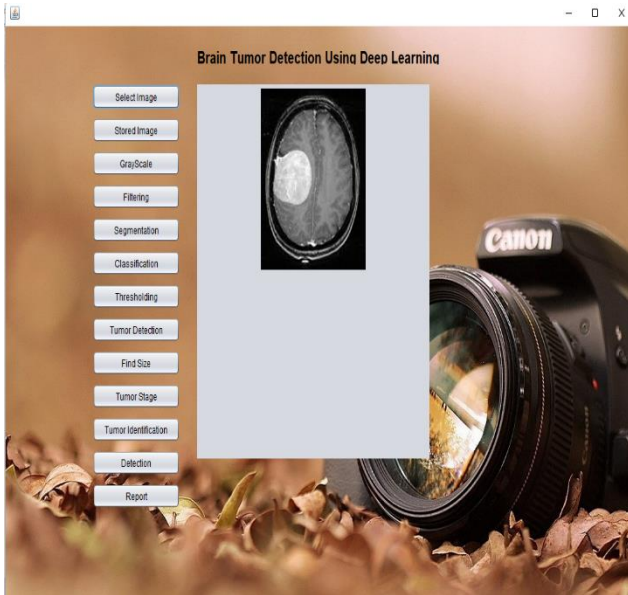
5. After login with valid credentials copy the URL and paste in another browser.

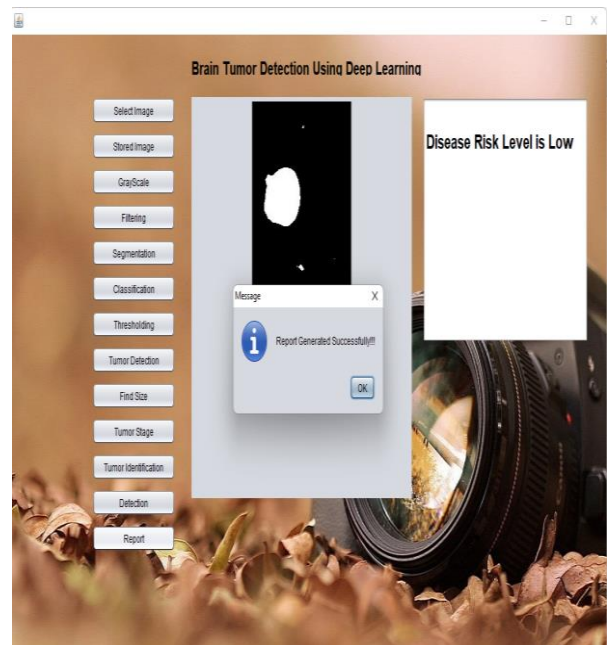
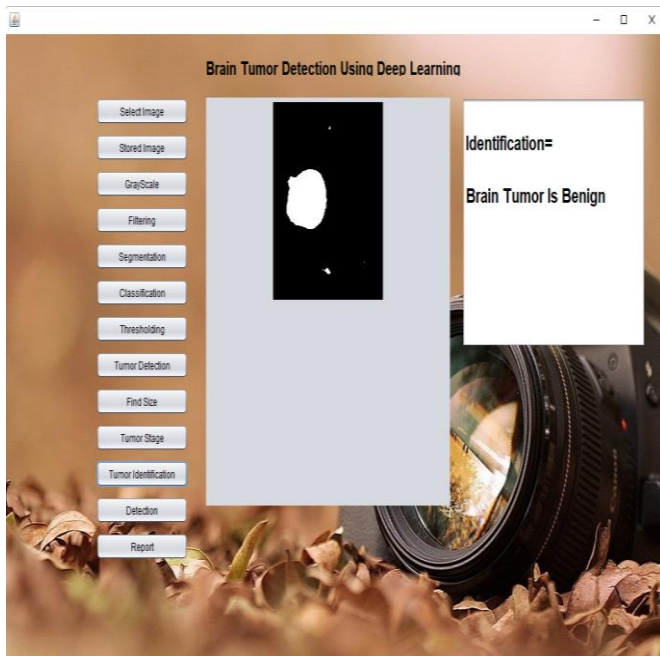
Expected: It should not display the user's welcome page.

6. Check the password with Lower case and upper case.

Expected: Password should be case sensitive.







VII.RESULT ANALYSIS

This the comparison between SVM and CNN. Existing System use SVM which gives less accuracy.

```
File Edit View Navigate Code Refactor Run Tools VCS Window Help ML - CNNNSVM.py
ML CNNNSVM.py
Project Files
  C:\ML
  .idea
  Brain_Dataset.csv
  augmented data
  tumorno
  tumoryes
  1 no.jpeg
Run: CNNNSVM
WARNING:tensorflow:From C:\Users\s\AppData\Local\Programs\Python\Python39\lib\site-packages\keras\src\utils\tf_utils.py:492: The name
WARNING:tensorflow:From C:\Users\s\AppData\Local\Programs\Python\Python39\lib\site-packages\keras\src\engine\base_layer_utils.py:384: T
938/938 [=====] - 9s 9ms/step - loss: 0.1788 - accuracy: 0.9477
Epoch 2/5
938/938 [=====] - 8s 9ms/step - loss: 0.0596 - accuracy: 0.9813
Epoch 3/5
938/938 [=====] - 8s 9ms/step - loss: 0.0396 - accuracy: 0.9880
Epoch 4/5
938/938 [=====] - 9s 9ms/step - loss: 0.0267 - accuracy: 0.9917
Epoch 5/5
938/938 [=====] - 9s 9ms/step - loss: 0.0200 - accuracy: 0.9937
CNN Accuracy: 0.9829000234603882
SVM Accuracy: 0.9792
CNN is better.
Process finished with exit code 0
```

Accuracy of our implementation using CNN Algorithm.


```
1 import os
2 import numpy as np
3 from skimage import io, color, transform
4 from scipy.ndimage import median_filter
5 from sklearn.model_selection import train_test_split
```

```
3/3 [=====] - 5s 1s/step - loss: 0.6898 - accuracy: 0.5294 - val_loss: 0.8005 - val_accuracy: 0.3182
Epoch 2/30
3/3 [=====] - 1s 501ms/step - loss: 0.6882 - accuracy: 0.5529 - val_loss: 0.7144 - val_accuracy: 0.3182
Epoch 3/30
3/3 [=====] - 2s 570ms/step - loss: 0.6763 - accuracy: 0.5529 - val_loss: 0.7365 - val_accuracy: 0.3182
Epoch 4/30
3/3 [=====] - 2s 523ms/step - loss: 0.6843 - accuracy: 0.5765 - val_loss: 0.7052 - val_accuracy: 0.3182
Epoch 5/30
3/3 [=====] - 1s 485ms/step - loss: 0.6745 - accuracy: 0.5647 - val_loss: 0.7814 - val_accuracy: 0.3182
Epoch 6/30
3/3 [=====] - 1s 508ms/step - loss: 0.6660 - accuracy: 0.5765 - val_loss: 0.6799 - val_accuracy: 0.5000
Epoch 7/30
3/3 [=====] - 2s 520ms/step - loss: 0.6614 - accuracy: 0.7529 - val_loss: 0.6920 - val_accuracy: 0.4091
Epoch 8/30
3/3 [=====] - 1s 507ms/step - loss: 0.6494 - accuracy: 0.6118 - val_loss: 0.7820 - val_accuracy: 0.3182
Epoch 9/30
3/3 [=====] - 1s 490ms/step - loss: 0.6555 - accuracy: 0.5529 - val_loss: 0.6983 - val_accuracy: 0.3636
Epoch 10/30
3/3 [=====] - 1s 511ms/step - loss: 0.6317 - accuracy: 0.6824 - val_loss: 0.6451 - val_accuracy: 0.8182
```



```
1 import os
2 import numpy as np
3 from skimage import io, color, transform
4 from scipy.ndimage import median_filter
5 from sklearn.model_selection import train_test_split
```

```
Epoch 10/30
3/3 [=====] - 1s 511ms/step - loss: 0.6317 - accuracy: 0.6824 - val_loss: 0.6451 - val_accuracy: 0.8182
Epoch 11/30
3/3 [=====] - 1s 487ms/step - loss: 0.6256 - accuracy: 0.7412 - val_loss: 0.6888 - val_accuracy: 0.4545
Epoch 12/30
3/3 [=====] - 1s 491ms/step - loss: 0.6154 - accuracy: 0.6471 - val_loss: 0.7282 - val_accuracy: 0.3636
Epoch 13/30
3/3 [=====] - 1s 499ms/step - loss: 0.6212 - accuracy: 0.6588 - val_loss: 0.6404 - val_accuracy: 0.6364
Epoch 14/30
3/3 [=====] - 1s 485ms/step - loss: 0.5868 - accuracy: 0.7647 - val_loss: 0.7410 - val_accuracy: 0.3636
Epoch 15/30
3/3 [=====] - 1s 471ms/step - loss: 0.5850 - accuracy: 0.6824 - val_loss: 0.6300 - val_accuracy: 0.6364
Epoch 16/30
3/3 [=====] - 2s 498ms/step - loss: 0.5639 - accuracy: 0.7412 - val_loss: 0.6008 - val_accuracy: 0.8182
Epoch 17/30
3/3 [=====] - 1s 467ms/step - loss: 0.5692 - accuracy: 0.7647 - val_loss: 0.6470 - val_accuracy: 0.6364
Epoch 18/30
3/3 [=====] - 1s 501ms/step - loss: 0.5674 - accuracy: 0.7059 - val_loss: 0.7193 - val_accuracy: 0.5000
Epoch 19/30
3/3 [=====] - 1s 470ms/step - loss: 0.5308 - accuracy: 0.7667 - val_loss: 0.5331 - val_accuracy: 0.8182
```

```

1 import os
2 import numpy as np
3 from skimage import io, color, transform
4 from scipy.ndimage import median_filter
5 from sklearn.model_selection import train_test_split

Epoch 19/30
3/3 [=====] - 1s 470ms/step - loss: 0.5398 - accuracy: 0.7647 - val_loss: 0.5331 - val_accuracy: 0.8182
Epoch 20/30
3/3 [=====] - 1s 470ms/step - loss: 0.5376 - accuracy: 0.7529 - val_loss: 0.6404 - val_accuracy: 0.6364
Epoch 21/30
3/3 [=====] - 1s 501ms/step - loss: 0.5123 - accuracy: 0.7647 - val_loss: 0.6811 - val_accuracy: 0.5455
Epoch 22/30
3/3 [=====] - 1s 466ms/step - loss: 0.5130 - accuracy: 0.7882 - val_loss: 0.6065 - val_accuracy: 0.6818
Epoch 23/30
3/3 [=====] - 1s 471ms/step - loss: 0.4997 - accuracy: 0.7529 - val_loss: 0.5965 - val_accuracy: 0.6818
Epoch 24/30
3/3 [=====] - 1s 479ms/step - loss: 0.4765 - accuracy: 0.7765 - val_loss: 0.6535 - val_accuracy: 0.6364
Epoch 25/30
3/3 [=====] - 1s 485ms/step - loss: 0.4799 - accuracy: 0.7882 - val_loss: 0.6254 - val_accuracy: 0.6364
Epoch 26/30
3/3 [=====] - 1s 461ms/step - loss: 0.4624 - accuracy: 0.7765 - val_loss: 0.5260 - val_accuracy: 0.9091
Epoch 27/30
3/3 [=====] - 1s 463ms/step - loss: 0.4576 - accuracy: 0.8118 - val_loss: 0.5761 - val_accuracy: 0.7273
Epoch 28/30
3/3 [=====] - 1s 463ms/step - loss: 0.4576 - accuracy: 0.8118 - val_loss: 0.5761 - val_accuracy: 0.7273
Epoch 29/30
3/3 [=====] - 1s 453ms/step - loss: 0.4507 - accuracy: 0.7647 - val_loss: 0.6764 - val_accuracy: 0.5455
Epoch 30/30
3/3 [=====] - 1s 473ms/step - loss: 0.4536 - accuracy: 0.7529 - val_loss: 0.5498 - val_accuracy: 0.8636
Test Accuracy: 81.48%
1/1 [=====] - 0s 87ms/step - loss: 0.4392 - accuracy: 0.8148
Accuracy: 81.48%
Process finished with exit code 0

```

```

1 import os
2 import numpy as np
3 from skimage import io, color, transform
4 from scipy.ndimage import median_filter
5 from sklearn.model_selection import train_test_split

Epoch 25/30
3/3 [=====] - 1s 479ms/step - loss: 0.4765 - accuracy: 0.7765 - val_loss: 0.6535 - val_accuracy: 0.6364
Epoch 26/30
3/3 [=====] - 1s 461ms/step - loss: 0.4624 - accuracy: 0.7765 - val_loss: 0.5260 - val_accuracy: 0.9091
Epoch 27/30
3/3 [=====] - 1s 463ms/step - loss: 0.4576 - accuracy: 0.8118 - val_loss: 0.5761 - val_accuracy: 0.7273
Epoch 28/30
3/3 [=====] - 1s 463ms/step - loss: 0.4576 - accuracy: 0.8118 - val_loss: 0.5761 - val_accuracy: 0.7273
Epoch 29/30
3/3 [=====] - 1s 453ms/step - loss: 0.4507 - accuracy: 0.7647 - val_loss: 0.6764 - val_accuracy: 0.5455
Epoch 30/30
3/3 [=====] - 1s 473ms/step - loss: 0.4536 - accuracy: 0.7529 - val_loss: 0.5498 - val_accuracy: 0.8636
Test Accuracy: 81.48%
1/1 [=====] - 0s 87ms/step - loss: 0.4392 - accuracy: 0.8148
Accuracy: 81.48%
Process finished with exit code 0

```

VIII. CONCLUSION

In approximate reasoning for calculating tumor shape and position calculation. Finally predict the disease risk from resultant area of tumor. i.e. predict Brain tumor risk level which is easier, cost reducible and time savable. There are different types of tumors are available. They may be as mass in brain or malignant over the brain. Suppose if it is a mass then K- means algorithm is enough to extract it from the brain cells. If there is any noise are present in the MR image it is removed before the K- means process. The noise free image is given as a input to the k-means and tumor is extracted from the MRI image. And then segmentation using K means for accurate tumor shape extraction of malignant tumor and thresholding of output in feature extraction. Finally approximate reasoning for calculating tumor area and position calculation and finally using the CNN classification technique to identify stage of tumor from resultant area of tumor. i.e. identify stage of tumor which is easier, cost reducible and time savable. Convolutional neural networks (CNNs) and deep learning have produced amazing outcomes in the identification of brain tumors. CNN models are capable of accurately identifying and classifying brain tumors, even tiny and subtle ones, because they can recognize complicated patterns in medical images. CNN-based brain tumor detection systems are a promising new technology that has the potential to greatly improve the lives of brain tumor patients, despite several drawbacks such as the requirement for vast volumes of labeled data and the possibility of overfitting. CNN-based brain tumor detection systems may help physicians plan and carry out difficult procedures by increasing the precision and efficacy of brain tumor diagnosis. The experimental results are compared with other algorithms.

IX. ACKNOWLEDGEMENTS

The present world of competition there is a race of existence in which those who have the will to come forward succeed. Project is like a bridge between theoretical and practical work. With this willing we joined this particular project. First of all, we would like to thank the supreme power the Almighty God who is obviously the one who has always guided us to work on the right path of life. We sincerely thank **Prof. R.H. Borhade** sir, Head of the Department of Computer Engineering of Smt. Kashibai Navale College of Engineering, for all the facilities provided to us in the pursuit of this project. We indebted to our project guide **Prof. S. P. Pingat**, Department of Computer Engineering of Smt. Kashibai Navale College of Engineering. We feel it's a pleasure to be indebted to our guide for her valuable support, advice and encouragement and we thank her for her superb and constant guidance towards this project. We are deeply grateful to all the staff members of the Computer Engineering department, for supporting us in all aspects. We acknowledge our deep sense of gratitude to our loving parents for being a constant source of inspiration and motivation.

X. REFERENCES

- [1] Samir Kumar Bandhyopadhyay and Tuhin Utsab Paul, "Automatic Segmentation of Brain Tumor from Multiple Images of Brain MRI" International Journal of Application or Innovation in Engineering & Management (IJAIEM), Volume 2, Issue 1, January 2013
- [2] A. Meena, "Spatial K-Means PET Image Segmentation of Neurodegenerative Disorder", A. Meena et.al / Indian Journal of Computer Science and Engineering (IJCSSE)
- [3] Suman Tatirajua and Avi Mehta, "Avoiding energy holes in wireless sensor networks with nonuniform node distribution," IEEE Trans. Parallel Distrib. Syst., vol. 19, no. 5, pp. 710–720, May 2008.
- [4] Ajala Funmilola A*, Oke O.A, Adedeji T.O and Alade O.M, Adewusi E.A, "Fuzzy k-c-means Clustering Algorithm for Medical Image Segmentation", Journal of Information Engineering and Applications ISSN 2224-5782 (print) ISSN 2225-0506 (online) Vol 2, No.6, 2012
- [5] Samir Kumar Bandhyopadhyay and Tuhin Utsab Paul, "Automatic Segmentation of Brain Tumor from Multiple Images of Brain MRI" International Journal of Application or Innovation in Engineering & Management (IJAIEM), Volume 2, Issue 1, January 2013
- [6] A. Meena, "Spatial K-Means PET Image Segmentation of Neurodegenerative Disorder", A. Meena et.al / Indian Journal of Computer Science and Engineering (IJCSSE)
- [7] Suman Tatirajua and Avi Mehta, "Avoiding energy holes in wireless sensor networks .
- [8] nonuniform node distribution," IEEE Trans. Parallel Distrib. Syst., vol. 19, no. 5, pp. 710–720, May 2008.
- [9] Ajala Funmilola A*, Oke O.A, Adedeji T.O and Alade O.M, Adewusi E.A, "Fuzzy k-c-means Clustering Algorithm for Medical Image Segmentation", Journal of Information Engineering and Applications ISSN 2224-5782 (print) ISSN 2225-0506 (online) Vol 2, No.6, 2012
- [10] Samir Kumar Bandhyopadhyay and Tuhin Utsab Paul, "Automatic Segmentation of Brain Tumor from Multiple Images of Brain MRI" International Journal of Application or Innovation in Engineering & Management (IJAIEM), Volume 2, Issue 1, January 2013
- [11] A. Meena, "Spatial K-Means PET Image Segmentation of Neurodegenerative Disorder", A. Meena et.al / Indian Journal of Computer Science and Engineering (IJCSSE)
- [12] Suman Tatirajua and Avi Mehta, "Avoiding energy holes in wireless sensor networks with nonuniform node distribution," IEEE Trans. Parallel Distrib. Syst., vol. 19, no. 5, pp. 710–720, May 2008.

- [13] Ajala Funmilola A*, Oke O.A, Adedeji T.O and Alade O.M, Adewusi E.A, “Fuzzy k-c-means Clustering Algorithm for Medical Image Segmentation”, Journal of Information Engineering and Applications ISSN 2224-5782 (print) ISSN 2225-0506 (online) Vol 2, No.6, 2012
- [14] M.H. Fazel Zarandia, M. Zarinbal and M. Izadi, “Systematic image processing for diagnosing brain tumors”, Department of Industrial Engineering, Amirkabir University of Technology, P.O. Box 15875-4413, Tehran, Iran , journal homepage: www.elsevier.com/locate/asoc
- [15] Samarjit Das, “Pattern Recognition using the K-means Technique” International Journal of Energy, Information and Communications Vol. 4, Issue 1, February, 2013
- [16] Vignesh Rajesh, Bharathan Venkat, Vikesh Karan and M. Poonkodi, “Brain Tumor Segmentation and its Area Calculation in Brain MR Images Using K-Mean Clustering and K-Mean Algorithm”, Department of Computer Science and Engineering, SRM University

