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# BRAIN TUMOR CLASSIFICATION

***Darsh Lukkad[1], Om Gujarathi[2], Manaswi Lukkad[3]***

*[1,2] Information Technology Department, Vishwakarma Institute of Information Technology, Pune, India.*

**Abstract- Brain tumours are among the most deadly and difficult to treat cancers, so early identification is crucial for enhancing patient outcomes. Recently, deep learning techniques have shown great promise in the identification and categorization of brain tumours from medical imaging data. In this investigation, we look at the use of deep learning methods for MRI brain tumour detection. We develop a convolutional neural network that can identify and classify several types of brain tumours based on their characteristics.**

**We evaluate the performance of our model using a publicly available dataset of brain tumours and contrast it with other state-of the-art techniques. Our results show that the suggested strategy works better and achieves excellent accuracy than other methods already in use. In order to improve patient outcomes and survival rates, our research shows the potential of deep learning approaches for enhancing the identification and diagnosis of brain tumours. The proposed method could be used in clinical settings to help in the early detection of brain tumours. Brain tumours must be discovered early for better patient outcomes.**

## I. INTRODUCTION

For the diagnosis and treatment of patients who may have a variety of illnesses impacting their brain function, brain disease detection is essential. Brain disorders like Alzheimer's, Parkinson's, multiple sclerosis, and stroke can significantly impair a person's quality of life and cause considerable impairment. Early diagnosis of these conditions can lead to better treatment outcomes, slower disease progression, and lessen the risk of additional brain deterioration.

Brain disorders can also significantly affect society as a whole, resulting in higher healthcare expenses and decreased productivity. Therefore, it is crucial for both individual and social well-being to create precise and trustworthy procedures for diagnosing brain illnesses.

Research and innovation can also serve as motivations for the discovery of brain disorders, as doing so can help to create novel cures and treatments by understanding the underlying mechanisms of these diseases. Early detection can also help identify populations that are at risk, allowing for the implementation of preventative measures and possibly lowering the occurrence of certain diseases in the future.

## II. PURPOSE AND OBJECTIVE

The research aims to carry out functions including classifying scans into several tumour types using CNN and assisting in the classification of brain tumours. On the application on the front end of our project, each of these options will be available. The suggested model would accept photos from the database, perform different pre-processing operations on these images to make the database more accurate and easy to classify, and then performance may be evaluated using other metrics and % correctness. The model will simplify the process of accurately classifying a huge number of photos.

Brain tumours are abnormal cell growths that can either be malignant or non-cancerous in the brain. Early diagnosis of brain tumours is crucial for effective treatment and better results. Brain tumor detection is necessary for several reasons:

· **Early Diagnosis**: Early detection of brain tumors can lead to better treatment outcomes. If detected early, treatment can begin before the tumor grows too large and causes damage to the brain.

· **Treatment Planning:** Detecting brain tumors can help doctors plan the best course of treatment for the patient. This can include surgery, radiation therapy, chemotherapy, or a combination of these treatments.

· **Preventing Spread**: Early detection can prevent the spread of the tumor to other parts of the brain or other organs in the body.

· **Monitoring Progression:** Regular monitoring of the tumor can help doctors determine if the treatment is working, or if changes in the treatment plan are necessary.

· **Improved Quality of Life:** Early detection and treatment can help patients maintain their quality of life and reduce the risk of disability caused by the tumor.

In summary, detecting brain tumors is crucial for timely diagnosis, treatment planning, preventing spread, monitoring progression, and improving the quality of life of the patient.

## III. LITERATURE SURVEY

**"Automatic Detection of Brain Tumor in MRI Images Using Convolutional Neural Networks"**[1] is a paper by S. Saha and S. Saha which appeared in the 2018 edition of the International Journal of Scientific and Engineering Research. The research suggests a deep learning-based method for MRI image based automatic brain tumour detection. The difficulty of brain tumour identification and the limits of current techniques are introduced at the outset of the paper. Convolutional neural networks (CNNs) are utilised in the suggested method for automatic brain tumour identification. The CNN architecture utilised by the authors in their method is described in depth. There are several convolutional layers in it, followed by fully connected and max-pooling layers. The CNN produces a binary classification identifying the presence or absence of a tumour and is trained using a collection of MRI images. The processes that were performed to prepare the data for the CNN training are also described in the study.

The MRI pictures have to be resized, normalised, and stripped of the skull. Using a dataset of 306 brain MRI scans, the authors ran tests to assess the effectiveness of their methodology. The findings demonstrated that the suggested method has a brain tumour detection accuracy of 93.46%. To verify the approach's efficacy, additional validation and testing on larger datasets are required.

**A Review on Brain Tumor Detection Using Image Processing Techniques"**[2] is a paper by K. N. Kishore and K. R. Manasa that was published in the Journal of Medical Systems in 2020. The report offers a thorough analysis of the various image processing methods applied to brain tumour identification.

The article provides a comprehensive overview of many image processing techniques used for brain tumour identification, including segmentation, feature extraction, and classification. The authors discuss various segmentation techniques, including active contour models, region-growing, and thresholding. They also go through different methods of feature extraction, such as wavelet transform analysis, shape analysis, and texture analysis. The article also covers alternative classification techniques such support vector machines, decision trees, and artificial neural networks.

The limitations and difficulties of current image processing methods for detecting brain tumours are also covered by the authors. These issues include the requirement for manual intervention, the diversity of tumour appearance, and the difficulty of telling tumours apart from other aberrant brain tissues.

The potential of machine learning methods, particularly deep learning, for enhancing brain tumour detection accuracy is highlighted in the paper's conclusion. The scientists point out that automatic segmentation and classification of brain tumours have shown encouraging results when using deep learning-based approaches, such as convolutional neural networks.

**"Deep Learning-Based Segmentation and Classification of Brain Tumor Using Magnetic Resonance Images"**[3] is a paper by M. S. Qaiser et al. that was published in the Journal of Medical Systems in 2018. The research suggests a deep learning-based method for classifying and segmenting brain tumours using MRI data.

The recommended technique automatically segments and classifies brain tumours using a convolutional neural network (CNN). The authors provide a detailed description of the CNN architecture they used in their method. There are several convolutional layers in it, followed by fully connected and max-pooling layers. A dataset of MRI images is used to train the CNN, and its output is a segmented image with a binary classification indicating whether or not a tumour is present. The processes that were performed to prepare the data for the CNN training are also described in the study. The MRI pictures have to be resized, normalised, and stripped of the skull.

Using a dataset of 285 brain MRI scans, the authors ran tests to assess the effectiveness of their methodology. The findings revealed that the suggested method classified brain tumours with an accuracy of 94% and an average Dice similarity coefficient (DSC) of 0.87 for segmenting brain tumours.

A deep learning-based technique for the segmentation and classification of brain tumours using MRI data is presented in detail in the paper. The results suggest that this technique may improve the accuracy and efficacy of brain cancer detection and may prove to be a helpful resource for doctors in the early detection, diagnosis, and treatment of brain tumours. Additional validation and testing on larger datasets are needed to confirm the effectiveness of the method.

**"Brain Tumor Detection and Segmentation Using Machine Learning Techniques: A Review"**[4] is a paper by S. Singh et al. that was published in the Journal of Medical Systems in 2020. The paper offers a thorough analysis of various machine learning methods for segmenting and detecting brain tumours.

The article provides a comprehensive overview of numerous supervised and unsupervised machine learning techniques applied to the identification and segmentation of brain tumours. The authors cover a wide range of supervised method types, including support vector machines, decision trees, random forests, and artificial neural networks. They also discuss unsupervised methods including k means clustering, fuzzy c-means clustering, and self-organizing maps. The research also discusses deep learning-based methods that have demonstrated promising outcomes in the autonomous segmentation and classification of brain tumours, such as convolutional neural networks and autoencoders. The authors also discuss the drawbacks and difficulties of current machine learning approaches for detecting and segmenting brain tumours, such as the requirement for sizable annotated datasets, the difficulty of overcoming class imbalance, and the requirement for feature engineering in conventional machine learning approaches.

The report continues by noting the need for additional research in this field as well as the promise of machine learning techniques for enhancing brain tumour identification and segmentation accuracy. The potential for deep learning-based strategies to increase the precision and effectiveness of brain tumour identification and segmentation is highlighted in this research. Researchers and doctors interested in the creation and implementation of machine learning methods for the detection and segmentation of brain tumours will find the review to be helpful.

## IV. NEED OF BRAIN TUMOR CLASSIFICATION SYSTEM

The aim of developing a brain tumor classification system is to accurately and efficiently classify brain tumors based on medical imaging data. The primary objectives of such a system include:

● **Improved Diagnostic Accuracy:** By offering an automated and standardised technique for tumour classification, the classification system seeks to improve the accuracy and reliability of brain tumour diagnosis. The method seeks to reduce diagnostic errors and increase overall tumour classification precision by utilising sophisticated machine learning or deep learning algorithms.

● **Facilitate Treatment Planning:** The classification method seeks to accurately classify brain tumours into distinct categories or subtypes in order to provide useful information for treatment planning and decision-making. Based on the discovered tumour features, this information can help medical practitioners choose the most suitable treatment approaches, such as surgery, chemotherapy, or radiation therapy.

● **Time-Efficient and Objective Assessment:** The goal of creating a brain tumour classification system is to offer radiologists a quicker alternative to manual evaluation. Automated classification can speed up workflow and cut down on the amount of time needed for diagnosis. Additionally, a standardised and objective classification strategy can aid in improving consistency and lowering inter-observer variability in tumour assessment.

● **Prediction of Prognosis and Patient Outcomes:** By finding particular tumour characteristics or biomarkers that are predictive of patient outcomes, the classification system may seek to include prognostic data. This enables more individualised treatment strategies and improved patient care by helping to forecast the tumor's aggressiveness, recurrence potential, or responsiveness to treatment.

● **Support Research and Development:** By offering a platform for data analysis and insight generation, the categorization system can help enhance brain tumour research and development. The method can help with investigations including tumour genetics, radiomics, or the prediction of treatment response, as well as with the identification of novel tumour subtypes and the identification of possible biomarkers.

V. PROPOSED SYSTEM ARCHITECTURE

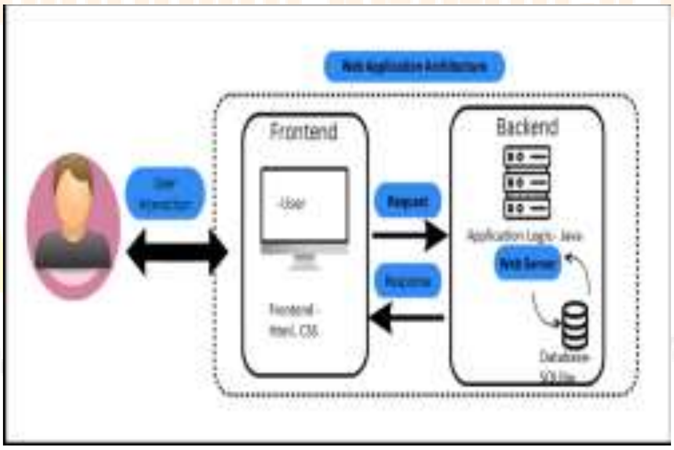

Fig.1. Proposed System Architecture

A web browser is used to visit our suggested web application, which is a piece of software that runs on a web server and is accessible online. A web application's architecture, as seen in Figure 1, typically consists of a server-side component (the web server and application) and a client-side component (the web browser). Client-side web UI pages are used by the user to interact with the programme, and the web browser makes requests to the server for particular resources. When a request is made, the server replies by returning the desired resources to the client's /Frontend page.

All the data records are stored in a structured way in SQL database. And we are using sql queries to do CRUD operations on the database. On the backend side, the web server receives requests from the client and forwards them to the application. The application processes the request and generates a response, which is then sent back to the client through the web server. To handle the request from client side all the logic is written in java which is helping to take necessary actions for particular requests from
users whether it is database operations or navigations through web pages.

Website is built using a variety of technologies, html, CSS, python, AI, etc. Then finally the UI gives an easy navigation experience allowing access to all the functionalities. Overall, the architecture of a web application is designed to allow users to interact with the application over the internet through their web browser, while the server-side components handle the processing and storage of data.

VI. METHODOLOGY

● **Dataset Collection:**

○ Assemble a sizable image collection of brain tumors.

○ A significant number of samples representing various tumor forms (such as gliomas, meningiomas, pituitary tumors, etc.) and non-tumor pictures should be included in this collection for comparison.

○ Make sure that the dataset is accurately labeled, with each image being designated as either a tumor image or a non-tumor image.

● For **data preprocessing** for brain tumor images. code includes the following steps: ○ The crop_img(img) function is defined to extract the region of interest (ROI) by applying image cropping based on contour detection.

○ Convert the input image (img) to
grayscale using cv2.cvtColor() function. ○ Apply Gaussian blur using cv2.GaussianBlur() function to reduce noise.

○ Threshold the grayscale image using cv2.threshold() function to obtain a binary image.

○ Perform morphological operations (erode and dilate) using cv2.erode() and cv2.dilate() functions to remove small regions and enhance the shape of the tumor.

○ Find contours in the binary image using cv2.findContours() function and retrieve the contour with the maximum area.

○ Determine the coordinates of the leftmost, rightmost, topmost, and bottommost points of the contour.

○ Define a constant ADD_PIXELS to add extra pixels around the contour.

○ Crop the original image using the coordinates of the contour and the added pixels to obtain the region of interest (ROI).

○ The code iterates over the training and testing directories, creating save paths for cleaned images.

○ For each image in the directories, the code reads the image, applies the crop_img() function to extract the ROI, and resizes the preprocessed image to a specified dimension.

○ The preprocessed images are saved in the corresponding directories.

○ The data preprocessing aims to enhance the quality of the images, removing unnecessary background and focusing on the tumor region. These processed images can then be used as input for further tasks such as classification using machine learning algorithms.

● **Model Architecture:**

○ As the foundation for the classification challenge, use the ResNet model. A deep convolutional neural network design called ResNet is renowned for its ability to handle challenging picture categorization jobs.

○ Use the ResNet model weights that have already been trained, such as ResNet-50 or ResNet-101, to benefit from the information found in expansive datasets like ImageNet.

○ Make adjustments to the ResNet model's final fully connected layer to correspond to the number of tumor classes in your dataset. The output for final categorization will be provided by this layer.

● **Model Training:**

○ The code defines a model architecture based on the ResNet50V2 pre-trained on ImageNet. The architecture includes average pooling, dropout, and dense layers for classification.

○ Model is trained by using following steps: ■ Apply average pooling using AveragePooling2D() with a pool size of (3,3) to reduce spatial dimensions. ■ Flatten the output using the Flatten() layer.

■ Add a dense layer with 64 units and
ReLU activation function using Dense() layer.

■ Apply dropout regularization with a rate of 0.2 using Dropout() layer.

■ Add a dense layer with 10 units and softmax activation for multi-class classification.

○ Set Trainable Layers:

■ Freeze the weights of the first few layers (except for the last 20 layers) in the base model to prevent their further training.

■ This can be achieved by setting layer.trainable = False for each layer in baseModel.layers[:-20].

○ Compile the Model:

■ Define the optimizer as Adam with a learning rate of 1e-4 and decay of 1e 4 / 200 using Adam() optimizer.

■ Compile the model by specifying the loss function as sparse categorical cross-entropy using SparseCategoricalCrossentropy()
from tf.keras.losses.

■ Choose the accuracy as the evaluation metric.

● **Model Evaluation:**

○ Use the test dataset, which it has never seen during training or validation, to evaluate the trained model.

○ To evaluate the performance of the model, compute evaluation measures

○ including accuracy, precision, recall, and F1-score.

○ To comprehend how the model classifies various tumor kinds, visualize and examine the confusion matrix.

## VII. IMPLEMENTATION


Fig.2. Get started page


Fig.3. Info page

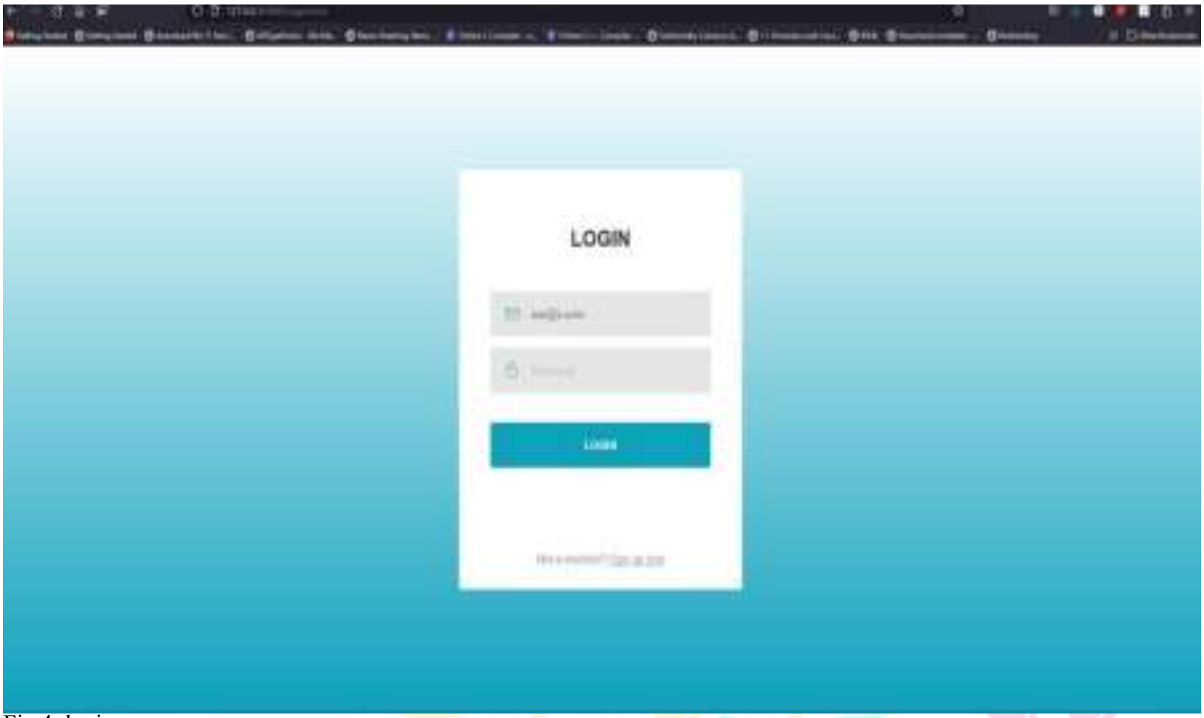


Fig.4. login page

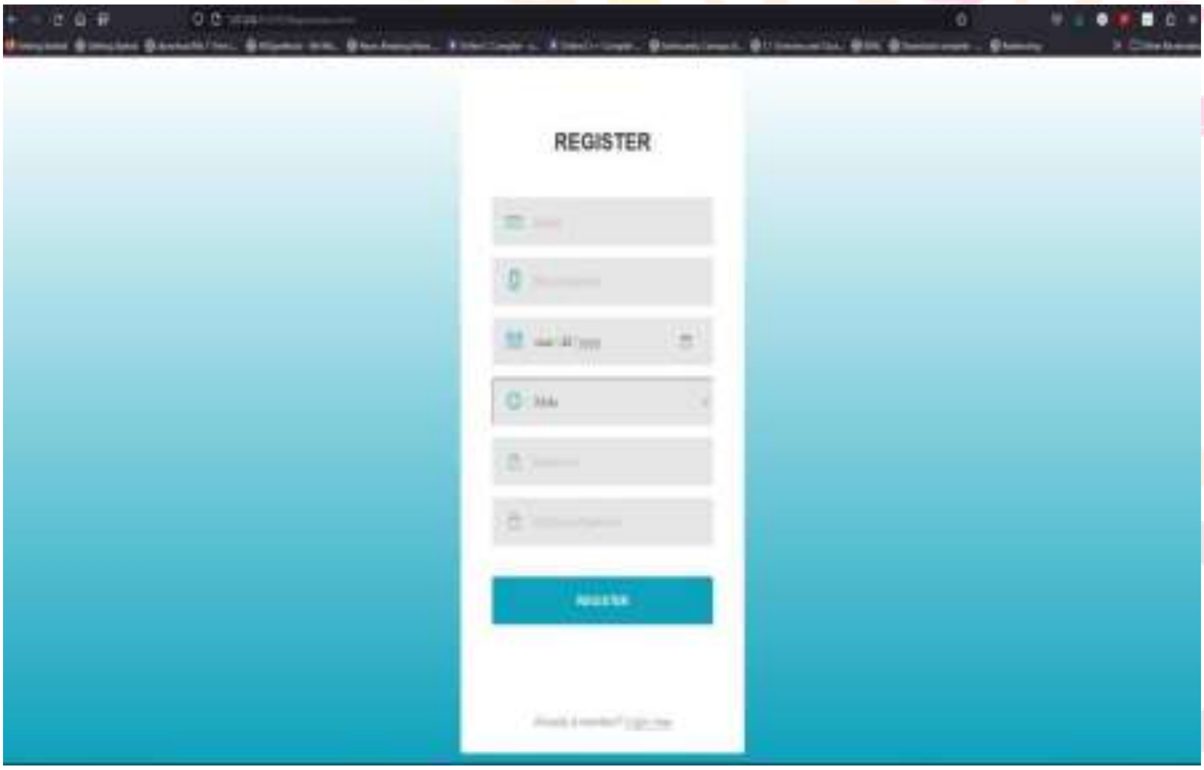




Fig.5. Register User


Fig.6. Home page

## VIII. RESULTS

Why this architecture?
Main objective of our project is to find if the uploaded image is having any kind of brain disease. This is a runtime thing; we take the MRI scan from the user and give the image to the model and display the disease name and confidence level. We do not save the image in our database and we only store the User details in our database. We have attached a screenshot below for the schema of the user table.


Fig.7. User Data Implementation

· Firstly, we applied CNN, but these models did not give the accuracy we wanted. · Then we applied transfer learning using a ResNet50 this model gave accuracy about 95%.

· As the data set was big enough, about 7000 images, we can use transfer learning using a ResNet50. With good computational power a good model with high accuracy can be trained.

## IX. CONCLUSION

In conclusion, the website for brain tumour classification is a priceless tool that is essential for the precise diagnosis and classification of brain tumours. This website offers a quick and accurate way to examine brain tumour photographs and classify them according to various categories using cutting-edge
algorithms and machine learning approaches.

The website offers several key benefits. Firstly, it enhances the speed and accuracy of tumor diagnosis, allowing healthcare professionals to make informed decisions quickly. By automating the classification process, the website reduces the risk of human error and enables more precise treatment planning.

Secondly, the website promotes standardization in brain tumor classification. With its consistent and objective approach, it helps ensure that diagnoses are reliable and consistent across different medical practitioners and institutions. This consistency is vital for effective collaboration and the advancement of brain tumor research.

Moreover, the website empowers patients by providing them with valuable information about their specific tumor type. By understanding the characteristics and prognosis associated with their tumor, patients can make more informed decisions regarding their treatment options and gain a better understanding of their condition. While this website represents a significant advancement in medical technology, it is important to note that it should be used as a supportive tool rather than a replacement for clinical expertise. The final diagnosis and treatment decisions should always be made by qualified healthcare professionals based on a comprehensive evaluation of all available information.

In summary, the brain tumor classification website revolutionizes the field of brain tumor diagnosis by offering a fast, reliable, and

standardized approach to classification. It has the potential to improve patient outcomes, enhance collaboration among medical professionals, and contribute to the overall understanding of brain tumors.

**X. FUTURE SCOPE**

In the proposed system some more functionalities can be added in the future. We are saving user history in the backend, which is not yet integrated with the frontend, which can be integrated further in the future scope.

Currently we are using a conventional database that is SQLite. In the future we can integrate our website with DB2 which is a high-performance database used by many big organizations.

As this project contains sensitive user data in future, we can plan to use blockchain for security. We have restricted this project with just Brain tumor detection. We can do some amends in the model and maybe we can use this for finding tumors in different parts of the body. We can also add a new type of User: doctor so that if a user gets detected with a tumor, then the website itself will suggest a few specialists they can talk to.

**XI. REFERENCES**

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