

BRAIN TUMOR DETECTION USING MACHINE LEARNING

INTRODUCTION:

A brain tumor is an abnormal growth of cells inside the brain. It may grow slowly or quickly and may be non-cancerous or cancerous [1]. Tumors in the brain press against nearby areas and affect the function of the body. This leads to different symptoms like headaches, memory loss seizures or changes in behavior [1]. Neurology is the study of the brain spinal cord and nerves. It helps to understand the structure and function of the nervous system. In technology the term neural network is used to describe a system made to act like the human brain. It is used to solve problems by learning from data. Brain tumor detection is a major problem in the field of healthcare. Early and accurate detection is very important for better treatment and survival of patients [1].

Several researchers have worked on brain tumor detection using different methods. Patro et al. used a combination of deep learning models and got an accuracy of over 96 percent in classifying brain tumors [2]. Hassan and Boulila used fuzzy thresholding and deep learning which improved the speed and accuracy of detection [3]. Thokar et al. used deep learning for segmenting medical images to find tumors and got very good results [4]. Anwar et al. applied transfer learning methods to MRI images and improved the precision of tumor detection [5]. Tariq et al. used Vision Transformers and EfficientNetV2 to detect multiple types of tumors with high accuracy [6]. These studies show that deep learning is very helpful in detecting brain tumors. However, most of them used very complex models or did not focus on reducing time and resource use. Some models are hard to use in small hospitals or with less computing power. Also, some studies do not give good results for all types of tumors. This creates a gap in research. We need a model that is simple fast and works for all types of tumors. Machine learning is able to solve this problem by learning from many brain images and making a system that is able to detect tumors quickly and with less cost [2][3][4][5].

The main objective of this research is to build a simple and fast system for detecting brain tumors using machine learning. This system is able to classify different types of tumors from MRI images. The goal is to help doctors to get fast and correct results. It is useful in hospitals, clinics and rural health centers where expert doctors or costly machines may not be available. The system is also able to be used in mobile apps or cloud services for faster help [2][5][6]. This research will help improve the life of patients by early detection and better treatment planning.

METHODOLOGY:

The project methodology involves collecting and preprocessing brain tumor image datasets. After preprocessing the images the next step is to build a Convolutional Neural Network model using the Keras Sequential API. The model includes convolutional layers with ReLU activation max-pooling layers and fully connected layers with a softmax activation function for multi-class

classification. The model is trained using the preprocessed training dataset and validated on a separate testing dataset to check its general performance.

Evaluation metrics such as accuracy loss precision recall and F1-score are used to measure the model performance. Visualization tools are used to better understand the learning process and output. The model that shows the highest accuracy and best performance is selected as the final model for brain tumor detection. This methodology uses machine learning to create a strong and reliable model that is able to help in the early detection of brain tumors and support doctors in making faster decisions.

DATA COLLECTION PROCEDURE:

For this study the brain tumor image dataset was collected from the Kaggle repository [7]. The dataset contains a total of 253 MRI images of the brain. Out of these 155 images show the presence of brain tumor and 98 images show no tumor. The dataset includes MRI images in grayscale format which are easy to process. The images are clearly labeled into two categories such as yes for brain tumor detected and no for brain tumor not detected. All images were carefully selected and organized to make sure the data is clean and suitable for training and testing machine learning models. The dataset helps to build an effective model for detecting brain tumors using image classification. The collection process ensures the data is balanced and supports reliable performance of the detection model.

DATA VALIDATION PROCEDURE:

The data validation procedure was used to check the reliability of the brain tumor image dataset. The process included checking the completeness and correctness of all images. It also checked if the data was organized properly and labeled correctly into yes and no categories. Any missing or unclear images were removed to make the dataset clean and useful. The dataset was also checked to make sure it followed ethical standards and had no sensitive or private information. These steps helped to make sure the dataset was ready and safe to use for training and testing in brain tumor detection.

DATA PREPROCESSING AND NORMALIZATION:

In the data preprocessing and normalization stage the brain tumor images were loaded and resized to a fixed size of 224x224 pixels. The images were converted to RGB format to keep the color information important for image classification. Each image was normalized by dividing the pixel values by 255 so that the values were between 0 and 1. This helped to improve the model training and make the learning process stable.

The labels yes and no were converted into numerical form using a label encoding method. This step helped the model to understand the classes. The images and labels were then changed into NumPy arrays for faster processing. This preprocessing and normalization process helped to prepare the data in the correct format so that the machine learning model was able to train effectively for brain tumor detection.

FEATURE EXTRACTION:

The feature extraction process used deep learning techniques to help the model learn and identify important patterns from the brain tumor images during training. The convolutional layers of the Convolutional Neural Network extracted features like edges, textures and shapes that are commonly found in brain tumor regions. These layers helped the model to understand different levels of detail in the images.

Max pooling layers were used to reduce the size of the feature maps while keeping the most important information. This made the training process faster and less complex. After that the features were flattened into a single vector using dense layers. This allowed the model to use the extracted features for final classification. This method helped the model to focus on key characteristics that showed the presence of a brain tumor and improved the accuracy of the classification process.

CLASSIFICATION ALGORITHMS:

In this project a Convolutional Neural Network model was used for the classification task of brain tumor detection. CNN is a type of deep learning model that is designed to work well with image data. The CNN architecture included several convolutional layers followed by max pooling layers that helped to reduce the image size while keeping the most important features. These layers allowed the model to automatically learn and extract features from brain MRI images such as edges shapes and textures.

After feature extraction the data was flattened and passed through dense layers which helped in classifying the images based on the features learned. The final layer used a sigmoid activation function which gave the probability of brain tumor presence. The model was trained using the Adam optimizer and binary cross entropy loss function to achieve accurate and efficient classification results.

DATA ANALYSIS TECHNIQUES:

Data analysis techniques used in this project focused on checking the performance of the trained Convolutional Neural Network model for brain tumor detection. The analysis included accuracy loss precision recall and F1-score to measure how well the model was able to detect brain tumors from MRI images.

A confusion matrix was also created to show the classification results by displaying true positive true negative false positive and false negative values. These metrics and visual tools gave clear understanding of how correctly the model was able to classify brain tumor and non-tumor cases. This analysis helped to confirm that the model was reliable and strong for use in real medical environments.

$$accuracy = \frac{\text{number of correct prediction}}{\text{number of total prediction}}$$

$$F1 \text{ score} = 2 \times \frac{\text{precision} \times \text{recall}}{\text{precision} + \text{recall}}$$

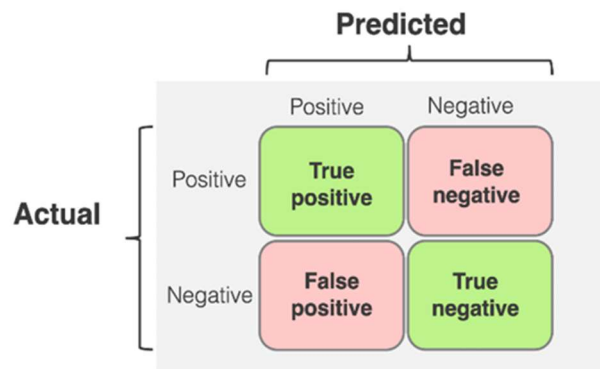


Figure 1 : confusion matrix

BLOCK DIAGRAM AND WORKFLOW DIAGRAM OF PROPOSED MODEL:

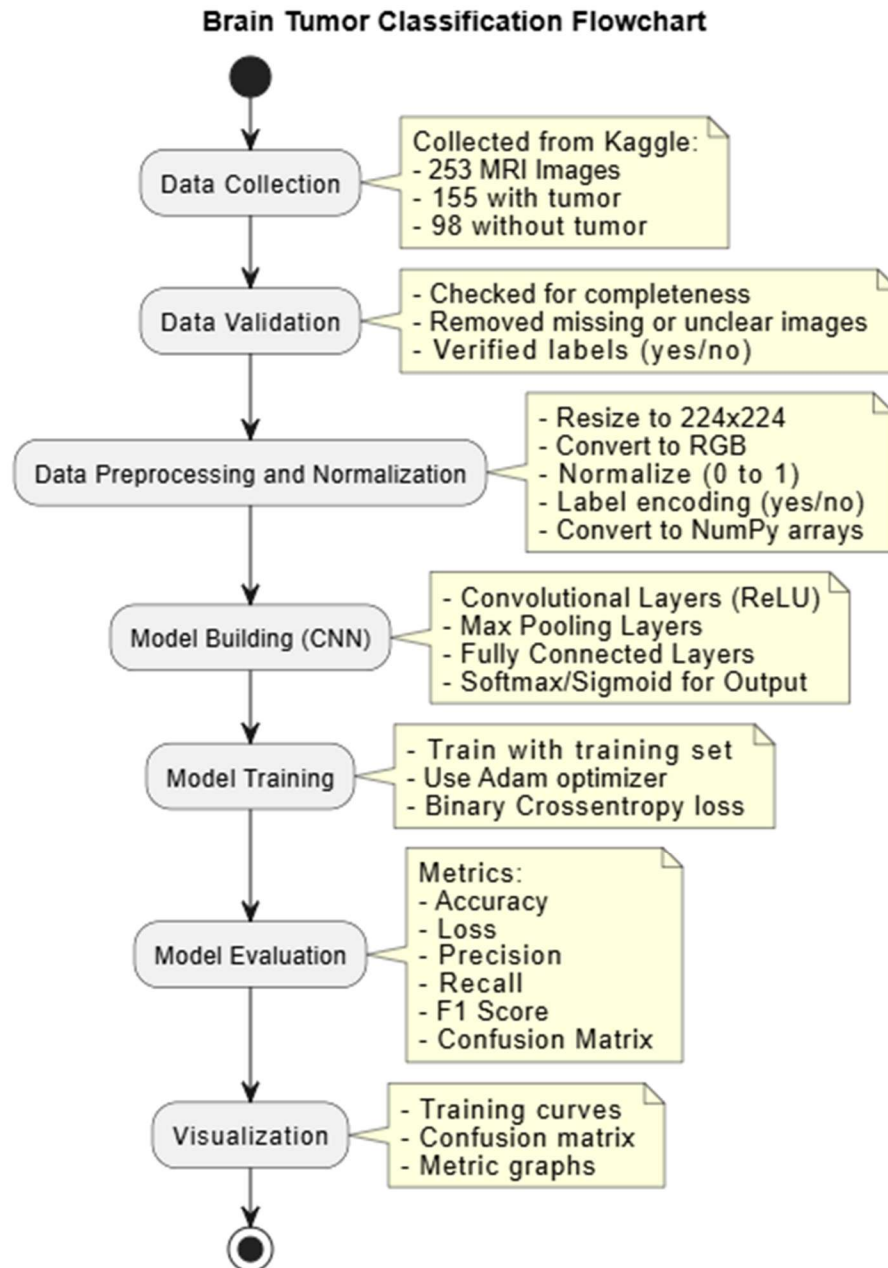


Figure 2: Workflow of Proposed Model

EXPERIMENTAL SETUP AND IMPLEMENTATION:

The model is implemented on Google Colab notebooks enabling users to write and execute Python code directly in a web browser.

RESULTS AND DISCUSSION:

The Convolutional Neural Network CNN model was used for brain tumor detection and classification. The dataset was divided into 70 percent for training and 30 percent for testing. The CNN model was trained on the training data and then tested on the validation data to evaluate its performance. The model showed good results with high accuracy and F1-score. These metrics indicate that the CNN was able to correctly identify brain tumor images and distinguish them from non-tumor images. Overall the CNN model demonstrated reliable performance in detecting brain tumors using MRI images.

| MODEL | ACCURACY | F1 SCORE |
|-------|----------|----------|
| CNN | 0.89 | 0.89 |

CONFUSION MATRIX ANALYSIS:

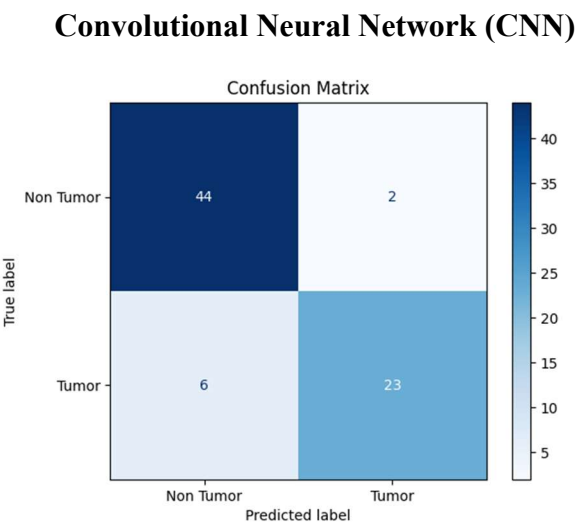


Figure 03: Confusion Matrix Analysis of CNN Model

The confusion matrix shows the performance of a brain tumor detection system. It correctly predicted 44 non tumor cases and 23 tumor cases. It wrongly predicted 2 non tumor cases as tumor and 6 tumor cases as non tumor. The system is able to detect non tumor cases with high accuracy.

RESULTS VALIDATION BY GRAPHICAL REPRESENTATION:

Accuracy graph CNN



Figure 04: Accuracy graph of training and testing

The graph shows the training and validation accuracy over 10 epochs. Training accuracy improves steadily and reaches above 90 percent by the final epoch. Validation accuracy increases quickly in the beginning and stays around 88 to 89 percent for most of the training. However it drops slightly after epoch 6 while training accuracy continues to rise. This indicates that the model may start overfitting after some epochs. Overall the model shows strong performance on both training and validation data.

Loss graph CNN

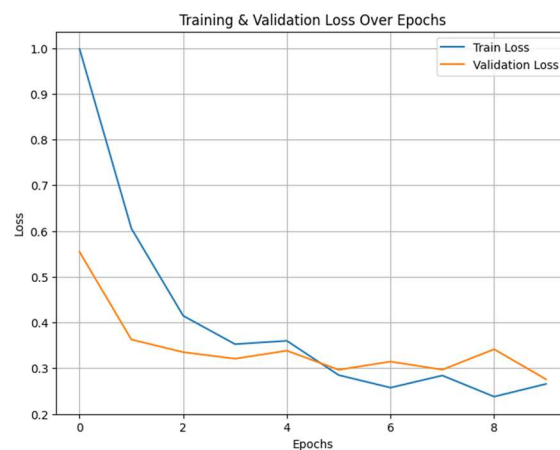


Figure 05: Loss graph of training and testing

The graph shows the training and validation loss over 10 epochs. Training loss decreases steadily from 1.0 to around 0.26. Validation loss also decreases at first and remains low between 0.28 and 0.36. After epoch 4 validation loss shows small fluctuations while training loss keeps improving. This suggests that the model is learning well but may begin to overfit slightly. Overall both losses are low which indicates good model performance.

CONCLUSION AND FUTURE RECOMMENDATIONS:

In conclusion the Convolutional Neural Network CNN model showed strong performance in detecting brain tumors using MRI images. The model achieved an accuracy of 89 percent and an F1 score of 0.89. These results prove that CNN is able to classify brain tumor and non-tumor images in a reliable way. The model learned key patterns from the data and provided consistent results during testing.

For future work the dataset should be expanded to include more images with different types of brain tumors. Using advanced methods like transfer learning with pre-trained models will be helpful to improve performance. Including domain-based knowledge such as tumor size and location may also increase accuracy. These steps will support the use of machine learning models in real medical systems and help doctors detect brain tumors at an early stage.

REFERENCES:

[1] Rana, R., Begum, S., Islam, M. R., Haque, M. A., & Rahman, M. M. (2022). Overview of brain cancer: its symptoms, diagnosis and treatments. *International Journal of Current Research and Review*, 14(11), 1–7.

- [2] S. G. K. Patro, N. Govil, S. Saxena, B. K. Mishra, A. T. Zamani, A. B. Miled, N. Parveen, H. Elshafie, and M. Hamdan, "Brain Tumor Classification Using an Ensemble of Deep Learning Techniques," IEEE Access, vol. 12, pp. 162094–162106, 2024.
- [3] N. M. H. Hassan and W. Boulila, "Efficient Approach for Brain Tumor Detection and Classification Using Fuzzy Thresholding and Deep Learning Algorithms," IEEE Access, vol. XX, pp. XX–XX, 2024, doi: 10.1109/ACCESS.2024.DoiNumber.
- [4] B. Thokar, B. Sapkota, B. R. Dawadi, and S. R. Joshi, "Medical Image Segmentation for Anomaly Detection Using Deep Learning Techniques," IEEE Access, vol. 12, pp. 143929–143943, Dec. 2024, doi: 10.1109/ACCESS.2024.3512664.
- [5] R. W. Anwar, F. Ullah, and M. Abrar, "Transformative Transfer Learning for MRI Brain Tumor Precision: Innovative Insights," IEEE Access, vol. XX, pp. XX–XX, 2025, doi: 10.1109/ACCESS.2025.3542451.
- [6] A. Tariq, I. Ahmad, M. M. Iqbal, and M. J. Iqbal, "Transforming Brain Tumor Detection: Empowering Multi-Class Classification With Vision Transformers and EfficientNetV2," IEEE Access, vol. XX, pp. XX–XX, 2025, doi: 10.1109/ACCESS.2025.3555638.
- [7] Navoneel Chakrabarty, "Brain MRI Images for Brain Tumor Detection," Kaggle, [Online]. Available: <https://www.kaggle.com/datasets/navoneel/brain-mri-images-for-brain-tumor-detection>