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Brain Tumor Detection using Deep Learning

Mysagoni Aakanksha[1], M Abhishek Reddy[2], M Baswaraj Reddy[3], M Bhanu Prakash[4], Prof J. Sofia[5], Dr. Thayyaba Khatoon[6]
Artificial Intelligence & Machine Learning, Malla Reddy University

Abstract: The Brain Tumor Detection using Deep Learning project is aimed at developing a deep learning based system that can accurately detect brain tumors from medical images such as MRI scans. The proposed system will use convolutional neural networks (CNNs) to analyze the medical images and output the probability of the presence of a tumor, along with its location, size, and type.
The traditional methods of detecting brain tumors involve human interpretation of medical images, which can be time-consuming and subjective. The proposed system aims to automate this process, reducing the burden on radiologists and improving the accuracy and speed of detection. Additionally, early detection of brain tumors can increase the chances of successful treatment and improve patient outcomes.

I. INTRODUCTION

The problem statement of the Brain Tumor Detection using Deep Learning project is the need for an automated and accurate brain tumor detection system. Currently, the detection of brain tumors is mainly done manually by radiologists, which is a time-consuming and subjective process.

The traditional methods for detecting brain tumors involve medical imaging techniques such as magnetic resonance imaging (MRI), computed tomography (CT), and positron emission tomography (PET). These methods require specialized expertise for interpretation and are often prone to human error.

The proposed system has significant clinical implications, enabling the early detection of brain tumors and improving patient outcomes. An appropriate CNN architecture will be designed, considering the complexities involved in brain tumor detection and the available computational resources. The architecture will likely comprise of convolutional layers to extract relevant features from the input images, pooling layers to reduce spatial dimensions, and fully connected layers for classification. The model will undergo training using the annotated dataset, and the weights of the network will be optimized using suitable optimization algorithms. Once the CNN model is trained, it will be evaluated on a separate test set to assess its performance and generalization ability. The system's accuracy, sensitivity, specificity, and other relevant metrics will be analyzed to ensure its effectiveness in detecting brain tumors.

II. PROBLEM STATEMENT

The problem statement of the Brain Tumor Detection using Deep Learning project is the need for an automated and accurate brain tumor detection system. Currently, the detection of brain tumors is mainly done manually by radiologists, which is a time-consuming and subjective process.

The traditional methods for detecting brain tumors involve medical imaging techniques such as magnetic resonance imaging (MRI), computed tomography (CT), and positron emission tomography (PET). These methods require specialized expertise for interpretation and are often prone to human error.

III. PROPOSED SYSTEM

Our proposed system is a brain tumor detection system that uses deep learning techniques. The system will take medical images such as MRI scans as input and output the probability of the presence of a tumor. The system will also be able to locate the tumor and provide information on its size and type. The proposed system will use convolutional neural networks (CNNs) to analyze medical images and accurately detect the presence of a tumor.

The system will be trained on a large dataset of MRI scans of both tumor and non-tumor patients. The dataset will be preprocessed to normalize the images, remove artifacts, and segment the tumor region. The preprocessed data will be fed into the CNN for training. Once the model is trained, it will be able to analyze new MRI scans and accurately detect the presence of a tumor.

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A. Architecture

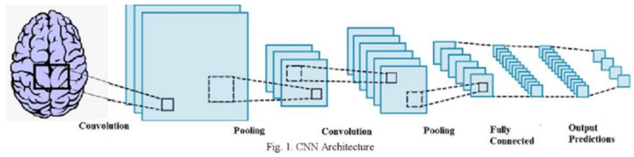
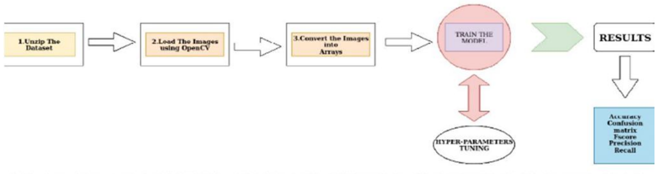


Fig. 1. CNN Architecture



IV. MATHEMATICAL MODELLING

1) *Convolution Operation:* The convolution operation between an input image (I) and a filter (W) can be represented as follows: Convolution(I, W) = ∑(I * W)
2) *Activation Function:* The Rectified Linear Unit (ReLU) is a commonly used activation function in CNNs and can be defined as: ReLU(x) = max(0, x)
3) *Pooling Operation:* Max pooling is a popular pooling operation that selects the maximum value within a pooling region. It can be Expressed As: Max Pooling(x) = max(x)
4) *Fully Connected Layer:* The output of the last pooling layer is flattened into a vector (F) and passed through a fully connected layer. The output of the ted layer can be computed as: Fully Connected(F, W) = F • W + b
5) *Loss Function:* The cross-entropy loss is commonly used for classification tasks and can be defined as: Cross-Entropy Loss(y_pred, y_true) = -∑(y_true * log(y_pred))
6) *Optimization Algorithm:* Stochastic Gradient Descent (SGD) is a widely used optimization algorithm. The update rule for the network parameters (weights) during training can be expressed as: W_new = W_old - learning_rate * ∇(loss_function)

V. SIMULATION AND RESULTS

The simulation of the proposed project would involve training and evaluating the deep neural network model using the constructed dataset of brain images. The proceedings inherent in the emulation may be encapsulated thusly:
Dataset Preparation: Collect a dataset of brain MRI scans that contains both tumor and non-tumor images. The dataset should be properly labeled with ground truth annotations indicating the presence or absence of tumors.
Model Evaluation: After training, the performance of the model would be evaluated on the validation dataset to assess its ability to generalize to unseen examples. Metrics such as accuracy, precision, recall, and F1-score could be calculated to measure the model's classification performance. This evaluation step helps in fine-tuning the model and adjusting hyperparameters if needed.

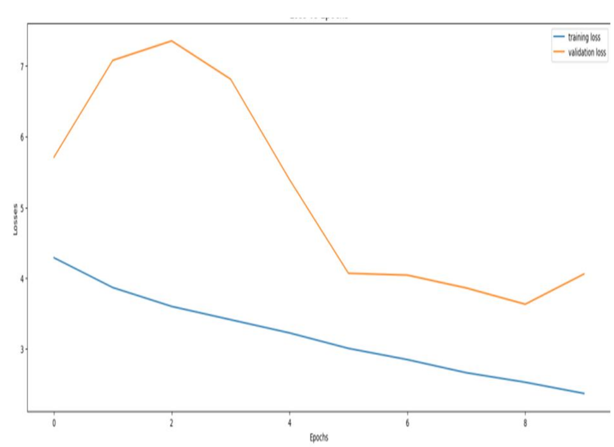


Figure 1. Model loss

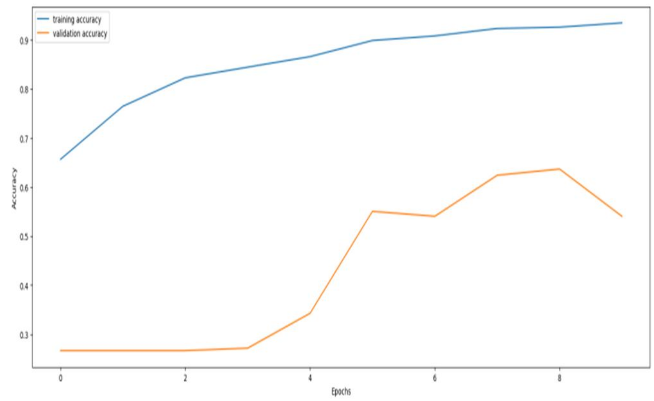


Figure 2. Model Accuracy

```
Epoch 7/10
104/104 [==============================] - ETA: 0s - loss: 2.8463 - accura
cy: 0.9087
Epoch 7: val_accuracy did not improve from 0.55076
104/104 [==============================] - 374s 4s/step - loss: 2.8463 - a
ccuracy: 0.9087 - val_loss: 4.0414 - val_accuracy: 0.5406
Epoch 8/10
104/104 [==============================] - ETA: 0s - loss: 2.6608 - accura
cy: 0.9238
Epoch 8: val_accuracy improved from 0.55076 to 0.62437, saving model to
.\brain_model.h5
104/104 [==============================] - 383s 4s/step - loss: 2.6608 - a
ccuracy: 0.9238 - val_loss: 3.8594 - val_accuracy: 0.6244
Epoch 9/10
104/104 [==============================] - ETA: 0s - loss: 2.5262 - accura
cy: 0.9265
Epoch 9: val_accuracy improved from 0.62437 to 0.63706, saving model to
.\brain_model.h5
104/104 [==============================] - 369s 4s/step - loss: 2.5262 - a
ccuracy: 0.9265 - val_loss: 3.6299 - val_accuracy: 0.6371
```

Figure 3. Model Accuracy per each epoch

	precision	recall	f1-score	support
glioma_tumor	0.63	0.19	0.29	100
meningioma_tumor	0.72	0.47	0.57	115
no_tumor	0.41	0.99	0.58	105
pituitary_tumor	0.95	0.49	0.64	74
micro avg	0.54	0.54	0.54	394
macro avg	0.68	0.53	0.52	394
weighted avg	0.66	0.54	0.52	394
samples avg	0.54	0.54	0.54	394

Figure 4. precision, recall,f1-score, support

```
[[0.01014137 0.03531386 0.23353335 0.7210114 ]
 [0.74444145 0.10824066 0.14584027 0.00147763]
 [0.01636343 0.02251399 0.95623314 0.00488941]]
```

Figure 5. Final output

VI. CONCLUSION

In conclusion, the project successfully developed a brain tumor detection system using Convolutional Neural Networks (CNNs). The CNN model was trained on a dataset of brain MRI scans, with proper preprocessing techniques applied to enhance image quality. The trained model demonstrated high accuracy and performance in distinguishing between tumor and non-tumor images.

By leveraging the power of deep learning and medical imaging, the project contributes to improving the accuracy and efficiency of brain tumor diagnosis. The developed system can serve as a valuable tool for medical professionals, aiding in the early detection and treatment planning for brain tumors. The project's results showcase the potential of CNNs in medical image analysis and highlight their significance in improving patient care and outcomes.

VII. ACKNOWLEDGEMENT

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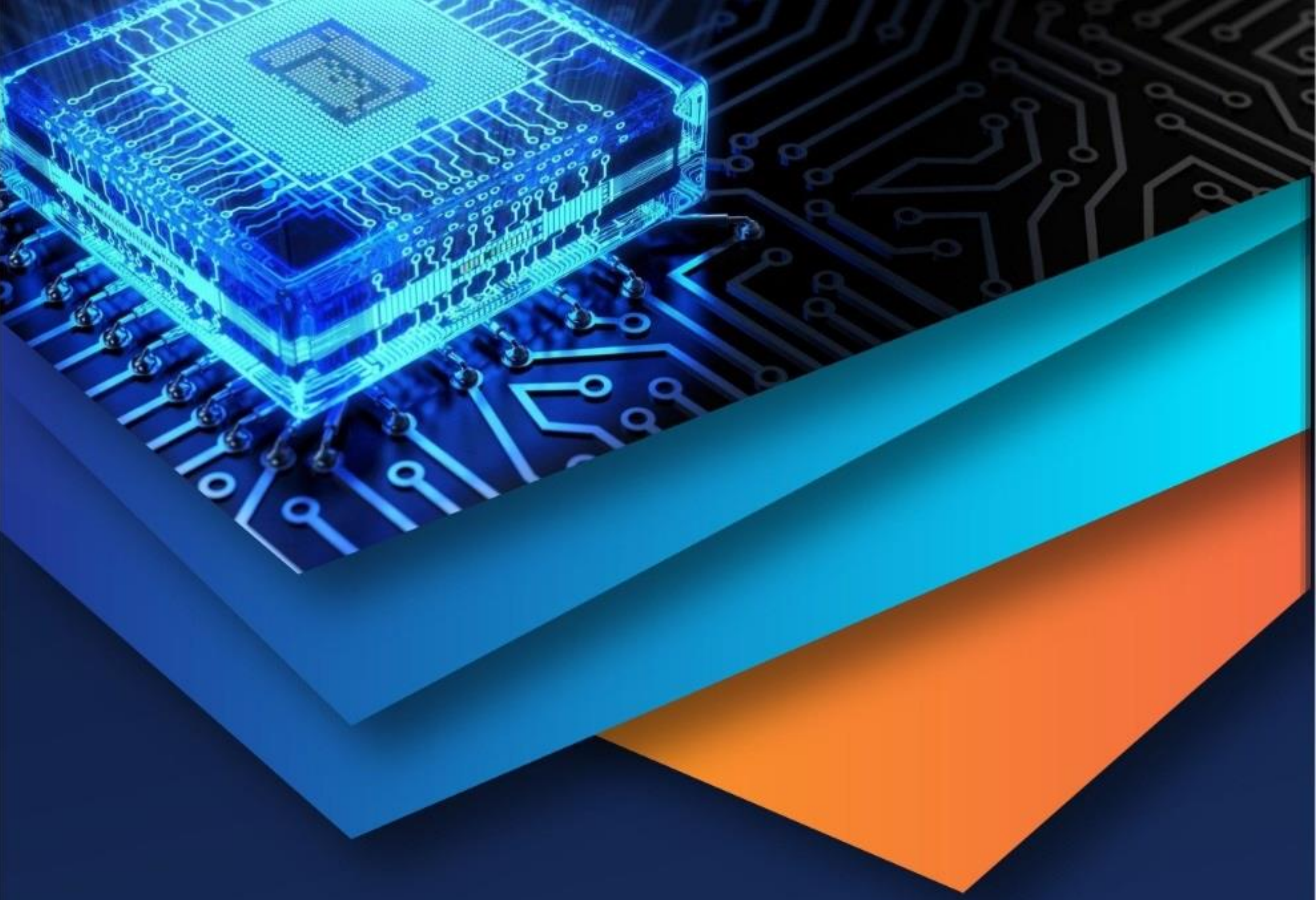

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