Brain Tumor Detection Using Deep Learning Techniques

Abstract—Detecting Brain Tumors in their early stages is very crucial. Brain tumors are classified by biopsy, which can only be performed via definitive Brain surgery. Computational intelligence oriented techniques can help physicians identify and classify brain tumor. Here, we proposed four deep learning methods and several machine learning approaches for diagnosing three types of tumor Glioma, Meningioma and Pituitary Gland Tumor, as well as, no tumors, using Magnetic Resonance Brain Images to enable physicians to detect with high accuracy tumors in early stages using a group of algorithms called "deep learning" which is a subset of machine learning. Deep learning means usage of AI neural networks which is layered to learn from large datasets, just like how brain of human processes information. With the help of MRI, we can utilize deep learning to create models for the detection and categorization of brain tumors and no tumor. This research investigates the application of deep learning techniques, specifically Convolutional Neural Networks (CNNs), for the automated detection and segmentation of brain tumors from MRI images. The dataset we have used is from Kaggle with over 5712 images used to train model, in which we have received the accuracy of 99.05(in percentage) using the model of Transformers Architectural Model

Index Terms—Brain Tumor,AI,ML,DL,CNN,DNN,MR Images

I. Introduction

Brain tumors are among the most deadly and debilitating neurological diseases due to the rapid and abnormal expansion of cells within brain tissue. Detection in time and accurate classification of brain tumors are essential to provide timely care and generate appropriate treatment plans. Traditional diagnostic approaches such as magnetic resonance imaging (MRI) and (CT) rely on radiologists to review and interpret multiple slices of images; this can be a laborious process and is associated with variability in human interpretations of medical imaging. To address these issues, automated brain tumor detection systems using artificial intelligence (AI) and deep learning approaches have gained considerable interest over the last few years.

Deep learning has shown exceptional promise for the analysis of medical images, given its ability to automatically extract multidimensional hierarchical features from raw data while requiring no predetermined features. To date, Convolutional Neural Networks (CNNs) have been applied to brain tumor detection tasks due to their salient spatial features and space organization modeling capabilities from medical images. However, Deep Neural Networks (DNNs) * further extend spatial feature capabilities through nonlinear transformations, which can improve model interpretation capabilities and classification. Lastly, advanced models such as Transformers and pretrained models such as VGG16 have recently exhibited better performance for image recognition tasks which could lead to their potential application for medical imaging tasks such as brain tumor detection.

This paper discusses the use of various deep learning models for detecting brain tumors: specifically CNN, DNN, transformer-based models, and VGG16. In addition, we propose a hybrid CNN+DNN model, which seeks to exploit the strength of CNNs in spatial feature extraction but additionally makes use of DNNs for classification to achieve a higher accuracy and robust performances. We systematically compare each of the methods to highlight their effectiveness, pros, and cons in brain tumor detection.

The contributions of this study can be summarized in two points: (1) we present and evaluate several state-ofthe-art deep learning architectures for brain tumor detection on MRI datasets; and (2) we present a hybrid CNN+DNN model that improves detection performance. The results of our experiments demonstrate the promise of combining deep learning methods for accurate and efficient decision support in the practice of clinical diagnosis. This will definitely help the unprivileged.

II. Literature Review

A. The section provides us with the previous research done by the scholars and the accuracy is in percentage

Sajid et al. introduced a hybrid CNN model[1] to detect brain tumors using BRATS MR images. The analysis and validation were performed on the effectiveness of a unique two-phase training method and sophisticated regularization approaches, such as dropout. Their suggested hybrid model combined two- and three-path networks, which enhanced the model's performance. The model may be effective for a variety of segmentation tasks, according to the capacity analysis of the CNNs, and better performance may be obtained with more training instances. After examining their model, they discovered that their Dice score was 86, their sensitivity was 86, and their specificity was 91

Wozniak et al. developed a cutting-edge correlation learning method (CLM) for deep neural network structures that integrates the CNN with a conventional architecture. Meningioma [1](708 images), glioma (1426 images), and pituitary (930 images) tumors were among the 3064 brain cancers they investigated. Their designed CLM model had an accuracy of around 96, a precision of about 95, and a recall of about 95. Garg et al. suggested the naive Bayes, random forest, neural network, KNN, and decision tree machine learning models for detecting brain tumors, as well as a

hybrid ensemble classifier (KNN-RF-DT)[5]. They evaluated the machine learning models using 2556 brain tumor images, with 85 of the data used for training and 15 for testing. For the classification, thirteen features were identified as a result of feature extraction by SWT, PCA, and GLCM. The proposed approach for identifying and categorizing brain tumors was evaluated, and the results showed that the method had an accuracy of 97.305 a precision of 97.73 a specificity of 97.60, a sensitivity of 97.04, and a reliability of 97.41

Khalil et al. proposed a modified two-step dragonfly algorithm for brain tumor segmentation using 3D MR images[4]. The greatest difficulties in identifying and segmenting the early stages of brain tumors are variations in the tumor size and structure. To overcome these challenges, the researchers employed a two-step dragonfly algorithm to precisely extract the original contour point. To obtain results using the proposed model, they used the BRATS 2017 3D MR brain tumor data set. They achieved an accuracy that was about 5 higher than that of the previous researchers, who performed a nearly identical study. To validate their findings, they also applied a variety of techniques, including fuzzy C-means, SVM, and random forests. To evaluate their results, they considered the metrics of the accuracy, precision, and recall. After evaluating their proposed model, they obtained an accuracy of 98.20, a recall of 95.13, and a precision of 93.21, which were better than the other models. The main weakness in this study was that the researchers only focused on the entire tumor segment, and they did not take into account many tumors per slice

Almadhoun et al. proposed a deep educational model using an MRI dataset for brain tumor detection. In addition to the deep educational model, they applied four other transfer learning models: VGG16[11], MobileNet, ResNet-50, and Inception V3. They used a dataset of 10,000 MR images with a 200 × 200 pixel resolution to evaluate their models. The dataset was divided into two categories with 5000 images each: brain tumors and non-brain tumors. Their proposed model, the deep educational model, performed better; the training accuracy was 100, and the test accuracy was 98

Methil et al. The goal of his paper was to develop a method that can improve the performance of CNN's image processing techniques when it comes to identify non-cancer and tumor images. Through various tasks, such as data augmentation and illumination, the paper was able to bring the tumor into focus. In order to improve the system's performance, a transfer learning procedure was performed. The project started with the ResNet101v2 image[15] processing model. Through further training, the system was able to achieve a 99.74 accuracy and a training recall of almost 99 percent. However, this method can potentially lead to errors since it relies on certain information about the tumor image. When creating an image, the size of the input should be set correctly so that it fits into the CNN model. If the input is not set correctly, it will not be able to fit into the image. In the future, the paper will perform various techniques to improve the system's capabilities.

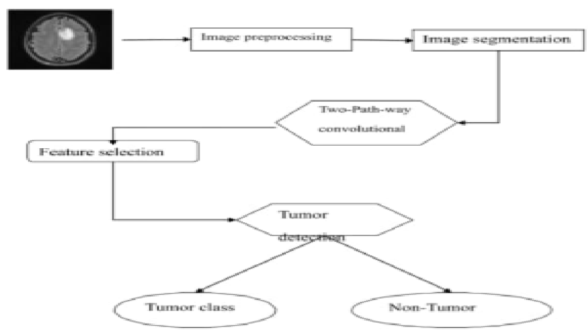
Srinivas et al.—The study utilized a novel transformer[8] design to improve the detection and classification of brain tumors. Through a combination of the firefly algorithm and an efficient image transformer, the model was able to achieve a 99.7 accuracy on Kaggle benchmarks. The goal of the FA was to optimize the hyperparameters of the DeiT model. This resulted in improved performance and decreased training loss. Although the results of the study are encouraging, further studies are needed to confirm its accuracy and explore the computational efficiency of the model.

Ahmed et al. The goal of this study was to design a Vision Transformer structure that can be used to classify different types of brain tumors. The ViT model was created by training it on its own and using advanced AI techniques to visualize its features. It performed well in a validated test, achieving a 91.61 accuracy rate, which was higher than the 83.37 of a comparable model[9]. The ViT model was trained using various AI techniques to visualize its features. It performed well in a validated test, achieving a 91.61 accuracy rate, which was higher than the 83.37 of a comparable model. While demonstrating strong performance, the study's limitations include the use of a single dataset, potentially limiting generalizability. Further validation on diverse datasets with varying image quality and tumor subtypes is necessary. Additionally, the computational demands of ViT models may pose challenges for real-time clinical application. Future research could explore model optimization strategies to address this limitation

III. Methodology

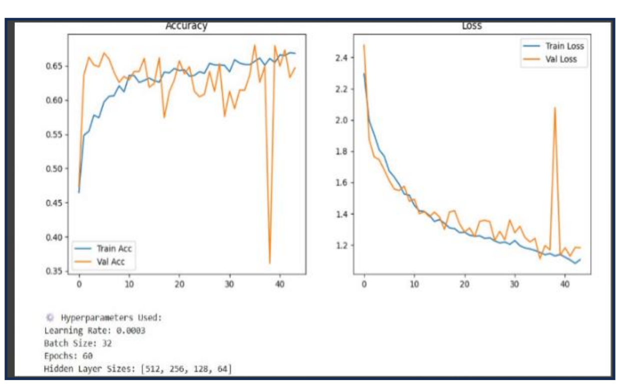
The methodology is divided into a few important stages. First, we collected our data from an available online source (kaggle.com). We have applied five different machine learning models to train our images. In our approach we have used image dataset from Kaggle along with Hyperparameter, Learning Rate, Batch Size, Hidden Size and Epochs[15]. For different algorithms we have used different epochs and Hyperparameter. All 5 parameters provide us with Recall, Precision , F1 Score, Accuracy (in percentage) CK Score and the 'p' value for the different 5 algorithms .The 5 algorithm we have used is CNN, DNN , VGG16, Transformers Architectural Model along with one hybrid model of CNN+DNN. The algorithms are as follows

A. Preprocessing Data To guarantee compatibility with deep learning models, every MRI image was resized to a consistent size. To enhance image quality, common preprocessing methods like contrast enhancement, noise reduction, and normalization were used. To improve dataset diversity and decrease overfitting, data augmentation techniques such as rotation, flipping, zooming, and shifting were used. After that, the dataset was split into subsets for testing, validation, and training in an 80:10:10 ratio.

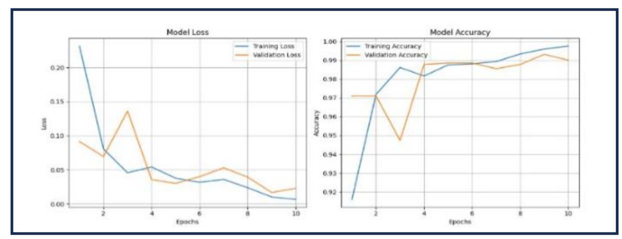


B. CNN, or convolutional neural network Because CNN performed well on image classification tasks, it was used as a baseline model. Multiple convolutional and pooling layers were used in the architecture to extract spatial features, and then fully connected layers were used for classification. Softmax was applied at the output for hidden layers using ReLU activation functions.An improved form of artificial neural networks (ANNs), convolutional neural networks (CNNs) are mainly used to extract features from grid-like matrix datasets. This is especially helpful for visual datasets where data patterns are important, like pictures or videos. Because CNNs are so good at processing visual data, they are frequently used in computer vision applications.

C. Deep Neural Network (DNN) The DNN model was developed in order to assess how well it performed in comparison to CNN. Multiple hidden layers of neurons with non-linear activation functions processed the flattened MRI images as input features. To enhance generalization, batch normalization and dropout were used. The model shed light on how fully connected architectures function with medical image data by concentrating on learning global feature representations as opposed to localized spatial features. It's a class of machine learning algorithms which is comparable to artificial neural networks and seeks to replicate how the brain processes information. Between the input and output layers, DNN shaves multiple hidden layers



D. Transformer Architectural Model In order to use selfattention mechanisms for tumor detection, recent developments in Vision Transformers (ViT) were integrated. Transformers, as opposed to CNNs, capture global dependencies throughout the entire image and process image patches as sequential tokens. The model was created using feed-forward networks, position embeddings, and multi-head self-attention layers.The transformer model is a kind of neural network design that is very effective for processing sequential data, especially as large language models (LLMs) come to mind. Furthermore, transformer models have performed at a high elite level in other areas of artificial intelligence (AI), such as computer vision, speech recognition, and time series forecasting.



Algorithms	Accuracy (%)	Precision (%)	F1-Score (%)
DNN	67.89	65.11	67.15
CNN	89.00	88.00	89.00
VGG16	93.03	93.54	93.01
Transformers Architectural Model	99.31	99.32	99.31
CNN + DNN	93	92	93

Table 1

E. Pre-trained Model VGG16 A well-known deep learning architecture, VGG16, was optimized for the detection of brain tumors. The final classification layers were swapped out and trained on the MRI dataset, while the pre-trained weights on ImageNet were used for feature extraction. By adapting to the medical imaging domain and utilizing prelearned visual features, transfer learning enabled the model to improve accuracy with limited data and drastically cut down on training time.Known for its ease of use and efficiency in image recognition tasks, the VGG16 model is a convolutional neural network (CNN) architecture with 13 convolutional layers, 3 fully connected layers, and 5 pooling layers a total of 16 weighted layers.

F. CNN+DNN Hybrid Model A hybrid model was created to combine the advantages of CNN and DNN. The first step involved extracting structural and spatial features from MRI images using CNN layers. For reliable decision-making, these extracted features were subsequently fed into a DNN classifier made up of fully connected layers.The CNN served as a feature extractor and the DNN as the decision-making engine during the end-to-end training of the hybrid CNN+DNN. The CNN and DNN components of this model worked in concert to provide strong spatial understanding of brain tumors and improve classification accuracy and deeper abstraction, respectively. Results from experiments showed that the hybrid architecture performed better than standalone CNN and DNN models in terms of accuracy, recall, and F1-score.

G. Instruction and Assessment For fairness, the same dataset split and hyperparameter tuning technique were used to train each model. Early stopping was used to avoid overfitting, and the cross-entropy loss function was utilized for optimization. To guarantee a thorough performance evaluation, the evaluation metrics included accuracy, precision, recall, F1score, and ROC-AUC. To demonstrate the efficacy of each strategy, comparative results of all models were examined, with an emphasis on the hybrid CNN+DNN framework, but the best result was given by Transformers Architectural model

IV. COMPARISON BASED ON ACCURACY FOUND

TABLE I

TABLE 1: PERFORMANCE COMPARISON OF DIFFERENT MODELS OF ALGO WE HAVE USED

V. DATASET USED/COLLECTION

We obtained the dataset from publicly accessible online data on kaggle.com to detect brain tumors. Images from magnetic resonance imaging (MRI) were used to construct the dataset. We selected MR images for our research since MRI is the best technique for detecting brain tumors. Meningioma (937 photos), no tumor (500 images), pituitary tumor (900 images), and glioma tumor (926 images) were the four different types of brain tumor data that we used in our study.The example of the dataset is given below :

Pre-Processing of the Dataset Pre-processing is an important step, where the data is processed to make it usable for training purposes. To highlight, since the MR images were obtained from a patient database, they were not clear and were of low quality. Thus, in order to prepare our images for further processing, we normalized them at this stage. In addition, the authors used Gaussian and Laplacian filters to smooth the images to remove the blurred images from the original images.

Data Division and Augmentation Our dataset was small and representative of only MR images, which is important to note since deep neural networks often rely on significantly larger datasets to obtain promising results. We had a total of 1311 MR images, of which 80 were used for training, and 10 of images were held out for testing and validated against remaining 10. The original dataset size can be expanded by applying augmentation, if large enough, in this case we were able to perform some data augmentation which would also improve training. While augmenting the dataset it would also be beneficial for the model's learning ability. Therefore, we augmented the dataset by mirroring the MR images and then performed rotation, width and height shifting, and zooming. We used the holdout validation method to validate the datasets.(All the numbers taken are in percentage) A number of critical performance metrics, including accuracy, precision, recall, and F1-score, are used to assess classification models in brain tumor detection. The confusion matrix, which comprises four terms—True Positives (TP), True Negatives (TN), False Positives (FP), and False Negatives (FN)—is used to calculate these metrics. TP stands for correctly predicted tumor cases, TN for correctly identified non-tumor cases, FP for healthy cases that were mistakenly classified as tumors, and FN for tumor cases that were mistakenly classified as non-tumor. By calculating the ratio of correctly classified cases to total cases, accuracy assesses the model's overall correctness. However, accuracy by itself could be deceptive in datasets that are unbalanced. By emphasizing positive class predictions, precision and recall overcome this constraint. Recall (also known as sensitivity) quantifies the percentage of correctly identified tumor cases out of all actual tumor cases, whereas precision is the percentage of correctly identified tumor cases among all cases predicted to be tumors. When class distribution is uneven, the F1-score provides a balanced measure of performance by combining precision and recall into a harmonic mean.

The performance metrics used in evaluating the models are defined as follows:

$$\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN} \quad (1)$$

$$\text{Precision} = \frac{TP}{TP+FP} \quad (2)$$

$$\text{Recall} = \frac{TP}{TP+FN} \quad (3)$$

$$\text{F1-score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \quad (4)$$

where TP = True Positives, TN = True Negatives, FP = False Positives, and FN = False Negatives. The graphs are given below:

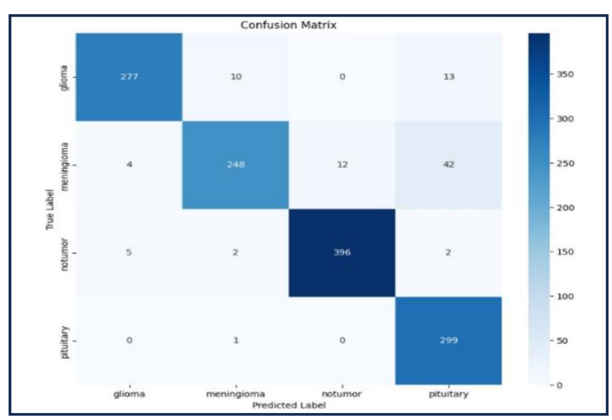


Figure showing the confusion matrix of Transformer architectural

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