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Brain Tumor Classification from MRI Scans via Transfer Learning and Enhanced Feature Representation

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ABSTRACT Brain tumors are abnormal cell growths in the central nervous system (CNS), and their timely detection is critical for improving patient outcomes. This paper proposes an automatic and efficient deep-learning framework for brain tumor detection from magnetic resonance imaging (MRI) scans. The framework employs a pre-trained ResNet50 model for feature extraction, followed by Global Average Pooling (GAP) and linear projection to obtain compact, high-level image representations. These features are then processed by a novel Dense-Dropout sequence, a core contribution of this work, which enhances non-linear feature learning, reduces overfitting, and improves robustness through diverse feature transformations. Another major contribution is the creation of the Mymensingh Medical College Brain Tumor (MMCBT) dataset, designed to address the lack of reliable brain tumor MRI resources. The dataset comprises MRI scans from 209 subjects (ages 9–65), including 3,671 tumor and 13,273 non-tumor images, all clinically verified under expert supervision. To overcome class imbalance, the tumor class was augmented, resulting in a balanced dataset well-suited for deep learning research. This curated resource provides a strong foundation for advancing brain tumor diagnosis, classification, and detection. Evaluated on both the newly created MMCBT dataset and the publicly available BTM benchmark dataset, the proposed framework demonstrates exceptional reliability. It achieves accuracies of 97.57% on the MMCBT dataset and 99.80% on the BTM dataset, along with consistently strong precision, recall, and F1-scores—metrics crucial for minimizing diagnostic errors in medical imaging. These results highlight the novelty of the framework and its potential as a robust clinical decision-support tool.

INDEX TERMS Brain Tumor, Deep Learning, Magnetic Resonance Imaging, CNN, Fully Connected Neural Network, Deep Feedforward Network.

I. Introduction

A Brain tumor is a collection of abnormal cells in the brain [1]. Brain tumors stand as a major concern in the field of medicine owing to the well-known complications and dire consequences. An early diagnosis is essential for successful treatment and long-term survival in patients with a brain tumor [2]. Historically, the diagnosis of brain tumors required human interpretation of medical images, and this process was not only slow but also susceptible to human errors. Recent advancements in technology have changed the game in brain tumor detection, and now, thanks to tools like Magnetic Resonance Imaging (MRI) and Convolutional Neural Networks (CNNs), it's never been easier to identify and diagnose brain tumors. The rapid development of deep learning technologies has greatly influenced the field of medical imaging, particularly with regard to detecting complex diseases such as brain tumors. The opportunity to use very powerful computational models in the analysis of medical image scans, in particular MRI scans, and the way they will transform diagnostic procedures. Early detection is crucial for increasing the survival rate of patients with brain tumors [2]; therefore, automatic and accurate brain tumor detection is essential for a better healthcare system [3] [4] [5]. Deep learning-based techniques have shown promising results for the detection and classification of brain tumors with high accuracy, thereby minimizing dependence on human expertise and time to diagnosis. Brain tumor detection relies on neural activities originating from thecomplexity and diversity of the human brain. These signals of the brain are interpreted through medical images such as MRI and CT Scan. These image modalities represent the spatial and intensity data of the brain tissues that appear in and around the tumor. The brain contains different types of tissues (gray matter, white matter, cerebrospinalfluid), and tumors may be benign or malignant [6] [7]. Neural activities that contribute to brain tumor differentiation rely on unusual tissue consolidation arrangements, texture distortions, shape, and abnormal ink shades in brain images [8]–[12]. The neural activity of the brain contributes significantly to the process of brain tumor formation, as well as to the detection through neuroimaging. Brain cells, the neurons, communicate with one another via electrical signals that govern basic body processes such as movement, memory, and pain sensation [13]. Erratic neural behavior, often resulting from brain tumors, may present in the form of seizures, paralysis, cognitive loss, and other neurologic signs [14]–[17]. In Imaging techniques, when MRI used to locate a brain tumor, it reveals physical changes to the structure of the brain such as tissue abnormalities, swelling or mass effect which is the pressure of a tumor on the surrounding brain. Furthermore, we can use MRI to measure changes in brain activity based on blood flow to specific locations in the brain [18], that helps determine how a tumor is affecting neural activities and interacting with other functions of the brain. This study aims to propose a deep learning-based method for brain tumor detection. By introducing Global Average Pooling (GAP) based feature extraction and Linear Projection (LP) based dimensionality reduction, the study seeks to provide improved overall accuracy, efficiency, and interpretability of brain tumor detection. The adoption of GAP allows for pooling of the global image features, and therefore, the computational cost is reduced compared with traditional methods.

Despite significant progress in brain tumor detection, several challenges remain in achieving high-accuracy and high-efficiency diagnoses [7], [13], [18]. MRI data is highly dimensional, making it computationally expensive to process. Additionally, datasets may have an imbalanced class distribution, leading to model bias, and many deep learning models are considered ”black boxes,” making it difficult for clinicians to trust their outputs. The main contributions of this work are summarized as follows:

- **Proposed Framework:** We introduce an automatic and efficient deep-learning framework for brain tumor detection from MRI scans, leveraging ResNet50 with Global Average Pooling (GAP) and linear projection for feature extraction, along with a novel Dense-Dropout sequence to enhance non-linear learning, reduce overfitting, and improve model robustness.
- **New Dataset:** We created the *Mymensingh Medical College Brain Tumor (MMCBT) dataset*, consisting of MRI scans from 209 subjects (ages 9–65), including 3,671 tumor and 13,273 non-tumor images, clinically verified under expert supervision. The dataset was balanced through augmentation and provides a valuable resource for advancing research in brain tumor analysis.
- **Performance Achievement:** The proposed framework achieves state-of-the-art performance, with accuracies of **97.57%** on the MMCBT dataset and **99.80%** on the public BTM dataset, along with strong precision, recall, and F1-scores, underscoring its potential as a robust tool for clinical decision support.

II. Literature Review

Recent studies have focused on using deep learning, especially convolutional neural networks (CNN), for the detection of brain tumors from magnetic resonance images.These methods are proven to be accurate and efficient with minimal reliance on human expertise. But some challenges, such as high-dimensional data, class imbalances, and model interpretability, still limit their complete clinical application. Early diagnosis is still a key factor in treatment outcome and patient survival. Ghazanfar Latif et al. [1] proposed a methodology to classify brain glioma tumor using Block-Based 3D Wavelet Features of MR Images. They have accomplished this work by multiclass. In this research study, the proposed Random Forest classifier, HGG and LGG respectively. In this work, they used 18600 MR images. Also, they acquired 89.75%,86.87%accuracy by using Random Forest classifier, HGG and LGG respectively that accuracy is very low. Neelum Noreen et al. [19] proposed a methodology to diagnosis brain tumor a deep Learning model based on concatenation. They have accomplished this work by Random features extraction. In this research study, the proposed Inception-v3 and DensNet201 classifier. This work used brain tumor dataset Figshare, which is publicly available. In this work, they produced 99.34 %, and 99.51% testing accuracies respectively with Inception-v3 and DensNet201. As they acquired high accuracy but they did not mention their Newly Created MMCBT Dataset. Arashdeep Kaur [3] proposed a methodology to extract brain tumor by using different segmentation method. He used a dataset of 25 MR Images of brain that used for testing the system and recording the experimental results. He did not mention any clear feature extraction method but he used Fuzzy c-means algorithm and acquired 90.57% accuracy that is very low accuracy. Gayathri S et al. [20] proposed a methodology to analyze, detect, and automatic classification of different stages of brain tumor. In this work, they used Support Vector Machine (SVM) classification method. They extract features such as color, shape and texture. In this work they use multiple data but did not mention any clear dataset. They acquired 98.03% accuracy. Khizar Abbas et al. [4] proposed a methodology to detect brain tumor using machine learning. They proposed LIPC based methodology for brain tumor classification and segmentation. They extract features such as vector size, standard deviation, histogram, kurtosis, and skewness. In this work, they used 3D brain tumor dataset. In this research work, they acquired 95% accuracy by using LIPC but they did not mention how much dataset they used for their research.

Sahar Ghanavati et al. [5] proposed a methodology to detect brain tumor by using MRI. In this research study, they use a multi-modality framework for automatic tumor detection. They did not mention any clear idea of dataset. They extract features such as intensity, shape deformation, symmetry, and texture features. In this work, they used Automatic tumor detection algorithm and acquired average accuracy of about 90% and that was not good. K N Deeksha et al. [21] proposed a methodology to classify brain tumor. In this work, they extract feature such as color, size, location, edge, shape. They used dataset which was collected from the website figshare, and it consists of 2,123 images of MRI scans of the brain although it's not their Newly Created MMCBT Dataset. In this research study, they used CNN algorithm and they acquired 93% for the training dataset and 92% for the testing dataset. Mahdis Roshanfekr Rad et al. [22] proposed a methodology to detect brain tumor. In this work, they used 3D MRI dataset but how much dataset they used it's not mentioned. They extract features such as lines, edges, and subjective contours. In this research study, they used (GLCU) and artificial neural network (ANN) Classification method. They acquired 98% accuracy that's very high. ADEKANMI A. ADEGUN et al. [23] proposed a methodology to detect and classify of skin lesions in dermoscopy images. The proposed model was evaluated on publicly available HAM10000 dataset of over 10000 images consisting of 7 different categories. In this work, they extract feature such as Local Binary Pattern (LBP), Edge Histogram (EH), Histogram of Oriented Gradients (HOG) and Gabor methods to extract color, texture, and shape. In this research study, they used FCN-based DenseNet classification method. They acquired 98% accuracy that's very high. V.P. GLADIS PUSHPA RATHI et al. [24] proposed a methodology to detect and characterized of brain tumor. In this work, they used HSOM, Wavelet packet feature extraction method. They used MRI dataset but how much dataset they used it's not mentioned. In this research study, they used ANN classification method and they required 96.6% accuracy. Khaleda Akhter Sathi et al. [25] proposed a methodology to classify brain tumor. In this work, they used Gabor + DWT + GLCM feature extraction method. They used a total of 180 images database for classification which is not huge. In this research study, they used ANN classification method and they required 98.9% accuracy which is very high. Sanjay Kumar C et al. [26] proposed a methodology to categorized brain tumor. In this work, they used 26 features out of which 13 are local and 13 are global are computed from GLCM and are utilized in training. They did not mention any clear idea about dataset. In this research study, they used SVM with Hybridized Local-Global Features classification method and they required 95% accuracy.

Muhammad Nazir et al. [27] proposed a methodology to detect brain tumor. In this work, they used Haar wavelet, DWT and DCT feature extraction method. They did not mention any clear idea about dataset. In this research study, they used DCT+NN and DCT+SVM classification method and they required 94.5% and 95% accuracy respectively. Hein Tun Zaw et al. [28] proposed a methodology to detect brain tumor. A total of 114 MRI images with 24 normal and 90 tumors are used for this research work. They extract feature such as used thresholding, edge detection, histogram equalization, segmentation. In this work, they used Naïve Bayes classification method and they acquired 94% accuracy. M. Monica Subashini et al. [29] proposed a methodology to analyze brain tumor. In this research work they used MRI images but did not mention any clear idea about data set how much dataset they used for their research. Also, they did not mention any clear idea about classification method and accuracy which is not good. Kang Han Oh et al. [30] proposed a methodology to detect brain tumors. [31] presents two deep learning methods and several machine learning approaches for accurately diagnosing brain tumors using MRI images. The proposed 2D Convolutional Neural Network achieved a training accuracy of 96.47%, demonstrating optimal performance compared to other methods, making it a valuable tool for clinical use In this research work, the scheme successfully detects the tumor region on the 60-brain magnetic resonance dataset. [32] introduces a novel two-module computerized method for brain tumor detection and classification from MRI images. The first module enhances images using adaptive Wiener filtering, neural networks, and independent component analysis, while the second module employs Support Vector Machines (SVM) for segmentation and classification. This research [33] addresses the challenging problem of brain tumor detection from MRI images by developing a novel deep learning architecture called EfficientNet-DbneAlexnet that combines EfficientNet with Deep batch normalized eLUAlexnet. In this work, they used SVM classification method but they did not mention any clear idea about accuracy which was very needed.

TABLE 1: Summary of the Newly Created MMCBT MRI Dataset

Class	No. of Subjects	No. of Images	After Augmentation
Tumor	63	3,671	13,252
Non-Tumor	146	13,273	13,273
Total	**209**	**16,944**	**26,525**

III. Dataset

In the study we used two dataset to evaluate the proposed model which describe below.

A. Newly Created Mymensingh Medical College Brain Tumor (MMCBT) Dataset

This dataset consists of brain tumor MRI images, collected from Mymensingh Medical College, Mymensingh, Bangladesh. The images were initially obtained in DICOM format and subsequently converted into JPEG format using Onis Viewer software for further analysis. The subjects ranged in age from 9 to 65 years, and included both male and female participants. Table 1 shows the summery of the newly created MMCBT dataset. In total, 209 subjects were considered, among which 63 were diagnosed with brain tumors and 146 were identified as non-tumor cases. The dataset contains 3,671 images of tumor cases and 13,273 images of non-tumor cases, each acquired at different imaging angles. All images were carefully labeled and verified by Dr. Md. Kamal Hossen, MBBS, BCS (Health), Resident Surgeon, Department of Neurosurgery, Mymensingh Medical College Hospital, under clinical supervision to ensure high-quality and reliable annotations. To address the class imbalance, the tumor class was augmented to 13,252 images, making the dataset balanced for deep learning applications. This curated dataset is particularly suitable for medical image analysis and deep learning studies, supporting research on the early diagnosis, classification, and detection of brain tumors.

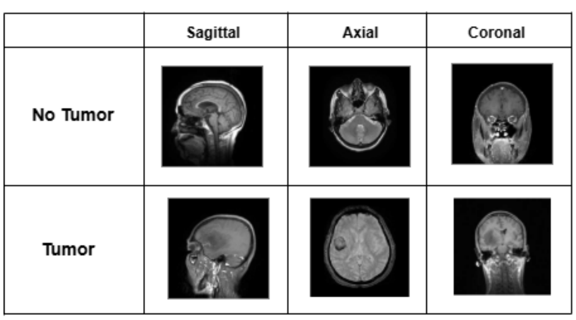


FIGURE 1: Different Sample of Brain Tumor of Newly Created MMCBT dataset

B. Brain Tumor Mendeley (BTM) Dataset

This dataset consists of Brain Tumor MRI images, collected from Mendeley Data [34]. In this dataset, original 7023 MRI images contained both tumor and non-tumor class, where 5023 images of Tumor cases and 2000 images of non-tumor cases. To balance the dataset, we augmented the non-tumor class data. Then, We have prepared our dataset, where non-tumor class contains 5024 images and total 10047 images contain augmented dataset.

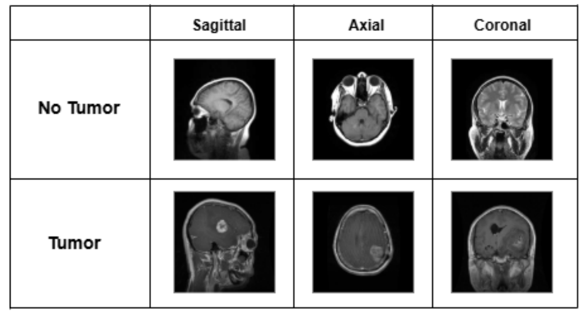


FIGURE 2: Different Sample of Brain Tumor of public BTM Dataset

IV. Proposed Method

The journey of our proposed method begins with MRI scans, where brain images are first collected and prepared for analysis. To make sense of these complex images, we employ a pre-trained ResNet50 model, which acts as a skilled observer, carefully extracting meaningful patterns from the scans. Instead of handling raw features directly, these patterns are refined using Global Average Pooling (GAP) and linear projection, producing compact, high-level representations that capture the essence of the data. Next, these representations are passed through a novel Dense-Dropout sequence, designed to act like a careful filter—strengthening useful signals, suppressing noise, and preventing the model from memorizing rather than learning. This stage ensures that the system generalizes well, even when faced with new and unseen cases. At the heart of this story lies the MMCBT dataset, a newly created collection of clinically verified MRI scans from 209 subjects. Balanced and comprehensive, it gives the model a strong foundation to learn the difference between tumor and non-tumor cases. Finally, when tested on both the MMCBT dataset and the public BTM benchmark, the method demonstrates outstanding performance.

A. Pre-processing

Preprocessing is an essential step in feature extraction from MRI images and begins after the image acquisition stage. The collected brain MRI data were initially stored in DICOM (Digital Imaging and Communications in Medicine) format, which is the standard format used in medical imaging. To ensure compatibility with commonly used image processing frameworks, the DICOM files were converted into JPEG format using Onis Viewer.

For each subject, MRI scans were acquired in three standard anatomical planes: Axial (top-to-bottom view), Coronal (front-to-back view), Sagittal (left-to-right view).

Each plane consisted of a series of slice images, capturing different cross-sectional views of the brain. On average, approximately 27 slices per plane were collected, resulting in 81 images per subject. After conversion, the images were systematically organized and labeled according to subject ID and anatomical plane. This preprocessing step ensured data uniformity, reduced format-related complexity, and prepared the dataset for subsequent analysis and model training. Then resized images to a fixed size for compatibility with neural network architectures, normalized pixel intensity values to standard ranges (e.g., $[0, 1]$ or $[-1, 1]$) to improve model convergence, and applied histogram equalization to enhance image contrast and highlight important features [23], [29]. Mathematically, the preprocessed image $\mathbf{P}$ can be expressed as $\mathbf{P} = h(\mathbf{I})$, where $h(\cdot)$ represents the set of preprocessing functions.

B. Feature Extraction via Transfer Learning

Feature extraction is an important step in which the system extracts the relevant features from the MRI image. The proposed method uses Global Average Pooling (**GAP**) and Linear Projection to densely subset features.

To capture discriminative spatial features, a pre-trained ResNet50 backbone (initialized on ImageNet) was employed. Unlike training from scratch, transfer learning leverages pre-learned low-level filters while fine-tuning high-level representations for brain MRI data. The final convolutional feature maps $F \in \mathbb{R}^{7\times7\times2048}$ were reduced via Global Average Pooling (GAP) to a 2048-dimensional vector:

$$\mathbf{F}_{\text{GAP}} = \frac{\mathbf{1}}{\mathbf{H} \times \mathbf{W}} \sum_{i=1}^{\mathbf{H}} \sum_{j=1}^{\mathbf{W}} \mathbf{F}_{i,j} \tag{1}$$

where H=W=7. GAP offers interpretability, computational efficiency, and reduced risk of overfitting compared with flattening approaches.

C. Linear Projection for Dimensionality Reduction

The pooled features were projected into a compact 512-dimensional space using a dense layer:

$$\boldsymbol{F_{proj} = W \,.\, F_{GAP} + b} \tag{2}$$

where $W \in \mathbb{R}^{512\times2048}$ and b is the bias term. This projection reduces redundancy while retaining task-relevant information, ensuring scalability for large MRI datasets.

Algorithm 1 Feature Extraction using ResNet50

Input:- Preprocessed image P of shape $(224, 224, 3)$
Output: 512-dimensional feature vector $F_{extracted}$

Step 1: Load pre-trained ResNet50 model without top layer
resnet50_model $\leftarrow$ `ResNet50(weights='imagenet', includ`

Step 2: Specify input tensor
X $\leftarrow$ `Input(shape=(224,224,3))`

Step 3: Pass input through ResNet50 to get feature map
F $\leftarrow$ `resnet50_model(X)`

Step 4: Apply Global Average Pooling (GAP) on $\mathbf{F} \in \mathbb{R}^{7\times7\times2048}$
$\mathbf{F_{GAP}} \leftarrow \frac{1}{7\times7} \sum_{i=1}^{7} \sum_{j=1}^{7} F_{i,j}$

Step 5: Apply a Dense layer to reduce dimension to 512
F_512 $\leftarrow$ `Dense(512)(F_GAP)`

Step 6: Define the final model
Final_Model $\leftarrow$ `Model(inputs=X, outputs=F_512)`

Step 7: Extract features from input image P
F_extracted $\leftarrow$ `Final_Model(P)`

Step 8: Return $F_{extracted}$
Return $F_{extracted}$

D. Classification

The extracted features are processed using a deep learning architecture, namely a deep feedforward network (DFN). While the primary experiments in this study are conducted with the DFN, additional experiments are also performed using CNN-1D and FCNN to further evaluate the robustness of the proposed approach.

1) DFN

Feedforward neural networks such as Multilayer Perceptron (MLP) are artificial models where information flow strictly progresses from the input through the hidden layers to the output. It is trained to estimate a rich representation of the data, with each layer being fully connected to the subsequent one. DFN can be applied to tasks such as classification and regression by learning the mapping from input features to output predictions.

In mathematical terms, each layer's output is obtained as a linear combination of its input, which is then passed through an activation function to provide the required non-linearity. In a neural network, the pre-activation value of a layer is computed as:

$$z^{(l)} = W^{(l)} a^{(l-1)} + b^{(l)}$$

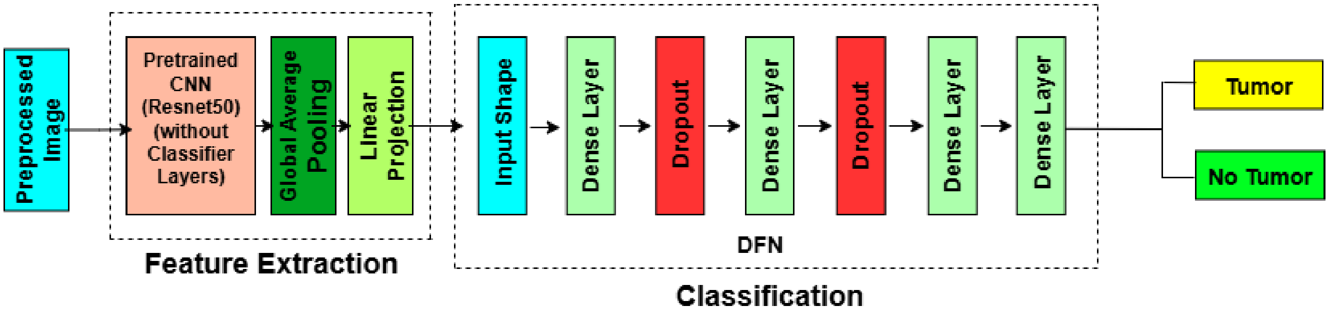


FIGURE 3: Illustrate the Proposed Method for GAP-Based Feature Extraction and Linear Projection.

The activation function is then applied element-wise to generate the layer's output:

$$a^{(l)} = f(z^{(l)})$$

Finally, the activation of the last layer produces the network's predicted output:

$$\hat{y} = a^{(L)}.$$

The network is trained by backpropagating the error of a loss function $\mathbf{L}$, which quantifies how close the predicted output is to the desired output. Optimization algorithms such as gradient descent and backpropagation are then applied to update the weights of the connections $\mathbf{W}^{(l)}$ and the bias terms $\mathbf{b}^{(l)}$, with the aim of minimizing this loss and improving the model's performance.

Denote the output of the DFN layer by $\boldsymbol{F_{final}}$. The likelihood of the brain tumor presence is represented by the sigmoid activation function:

$$\mathbf{P} = \boldsymbol{\sigma}\left(\mathbf{F}_{\text{final}}\right) \tag{3}$$

Where $\boldsymbol{\sigma}(x)$ is the sigmoid activation function as follows:

$$\sigma(x) = \frac{1}{1+e^{-x}} \tag{4}$$

The final decision can be made based on the probability output $\boldsymbol{p}$.

$$y = \begin{cases} 1, & \text{if } p > 0.5 \text{ (tumor detected)} \\ 0, & \text{if } p \leq 0.5 \text{ (no tumor detected)} \end{cases} \tag{5}$$

E. Optimization and Training Setup

The model was optimized using the Adam optimizer with a learning rate of 1×10^{-4}, binary cross-entropy loss, and mini-batch size of 32. Early stopping and learning rate scheduling were employed to prevent overfitting. On average, training converged within 25–30 epochs

V. Result and Discussion

In the study, we applied the Resnet50 with Global Average Pooling and linear projection to extract features. Then we applied DFN to reduce the feature and classification. The models were evaluated with 2 datasets, where each dataset was assessed based on accuracy, precision, recall, and F1-score.

A. Evaluation Metrics

Evaluation metrics are used to evaluate the performance of the models compared to other models' performance.

$$\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN} \tag{6}$$

$$\text{Precision} = \frac{TP}{TP+FP} \tag{7}$$

$$\text{Recall} = \frac{TP}{TP+FN} \tag{8}$$

$$F1-score = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \tag{9}$$

B. Ablation Study

Beside DFN we also applied other combinations of deep learning to observe the classification accuracy rate. 1D CNN and FCNN are describe below as the classifier.

1) 1D CNN

The 1D CNN body takes a feature vector resulting from GAP and conducts convolution-based operations to capture the spatial hierarchies of the features [35] [36] [37]. Because the input is 1D (i.e., vector after GAP), the Convolution down-samples and captures local patterns. 1D Convolution over an input 1D tensor:

$$\mathbf{F}_{\text{conv}}(t) = \sum_{k=1}^{K} \mathbf{W}_k \cdot \mathbf{F}_{\text{avg}}(t+k) + b \tag{10}$$

Where $\boldsymbol{W_k}$ is the Convolution kernels, $\boldsymbol{t}$ is the timestep index, and $\boldsymbol{K}$ is the number of filters.

2) FCNN

FCNN is an ordinary feedforward neural network with a number of layers in which all the neurons in the layer are connected to all the neurons in the next layer [23]. The FCNN processes these features in another way and produces the final prediction. The forward function of a fully connected layer can be formulated as:

$$\mathbf{F}_{\text{next}} = \mathbf{W} \cdot \mathbf{F}_{\text{prev}} + b \qquad (11)$$

Where $\boldsymbol{W}$ is the weight matrix and $\boldsymbol{F_{prev}}$, $\boldsymbol{F_{next}}$ are feature vectors in the previous layer and the output of the current layer, respectively.

C. Performance of Newly Created MMCBT dataset:

1. **1D CNN** : The 1D CNN model achieved an accuracy of **95.85%,** where precision of **96.33%,** recall of **95.15%,** and an F1-score of **95.74%.** While the model performed well, there is room for improvement in terms of recall.
2. **FCNN**: The Fully Connected Neural Network (FCNN) model outperformed 1D CNN with an accuracy of **97.44%,** precision of **96.03%,** recall of **98.73%,** and F1-score of **97.36%.** The increase in recall shows the model's stronger ability to identify positive instances.
3. **DFN**: The Deep Feedforward Network (DFN) classifier demonstrated the best performance with an accuracy of **97.57%,** precision of **96.67%,** recall of **98.42%,** and an F1-score **of 97.54%.** This classifier exhibited the highest accuracy and strong precision and recall values.

TABLE 2: Performance of Newly Created MMCBT dataset

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
1D CNN	95.85	96.33	95.15	95.74
FCNN	97.44	96.03	98.73	97.36
DFN	97.57	96.67	98.42	97.54

Figure 5 and Figure 6 describe the training and validation accuracy and loss. In 1D CNN model, It achieved 99.97% training accuracy and 95.85% validation accuracy from where at the same time the training loss 0.12% is and validation loss is 27.06%. In FCNN (Fully Connected Neural Network) model achieved 99.89% training accuracy and 97.44% validation accuracy, where at the same time the training loss 0.34% is and validation loss is 16.3%. In DFN model also describe the training and validation accuracy and the training and validation loss of CNN. It achieved 99.82% training accuracy and 97.57% validation accuracy, where at the same time the training loss 0.50% is and validation loss is 14.34%.

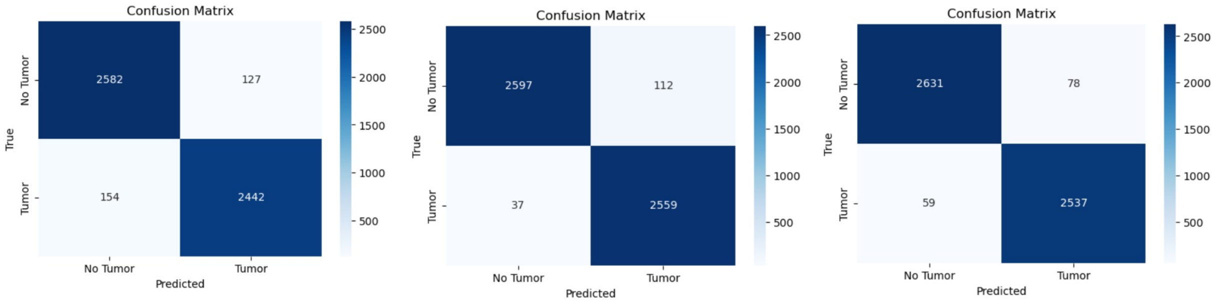
The table 3, presents several research efforts along with their corresponding classification models and the accuracy they achieved. It includes multiple studies conducted by various authors who applied different machine learning methods to classification tasks. Each entry lists the author names along with the classifiers used and the accuracy results. The research incorporates a range of classifiers, including k-means clustering, SVM, RBF Neural Networks (NN), Deep Neural Networks (DNN), Convolutional Neural Networks (CNN), AlexNet, Naïve Bayes, LIPC, fuzzy c-means, and other modern techniques such as 1D CNN, Fully Convolutional Neural Networks (FCNN), and Deep Feature Networks (DFN). The classifiers achieved accuracy rates between 83% and 97.5%, with the highest performance recorded by the proposed models: 1D CNN at 95.85% and DFN at 97.5%

The Table 4 analysis of the dataset reveals that DFN performs the best with the highest accuracy of 97.57% and relatively fast processing times, taking only 8 seconds per epoch and 193 ms per image. FCNN follows closely with an accuracy of 97.44%, being the fastest in terms of training time at just 7 seconds per epoch, though its test time per image is slightly slower at 184 ms. CNN-2D also achieves a high accuracy of 97.15% with a fast test time of 197 ms, but it takes 1429 seconds per epoch, which is slower compared to FCNN and DFN. On the other hand, ResNet50 and VGG16 show moderate accuracies of 96.77% and 96.55%, respectively, but they are significantly slower, particularly in testing, with ResNet50 taking 700 ms per image and VGG16 taking 377 ms. DenseNet121 has the lowest accuracy of 89.14% and also has the slowest performance, with a test time of 1300 ms per image and a training time of 1390 seconds per epoch, making it the least efficient among the models.

Figure 7 shows that the time taken of training to complete each epoch shows a wide range across different models.It can be observed that CNNs such as ResNet-50 and VGG16 have the highest training times, 1623 and 1541 seconds, respectively, due to their computational complexity. CNN-2D and DenseNet-121 also consume considerable elapsed time, logging 1429 and 1390 seconds per epoch. The CNN-1D model is significantly faster, taking only 45 seconds. FCNN and DFN are the two fastest models to train, taking 7 and 8 seconds per epoch due to their light design and quick convergence. In general, this dataset yields longer training times for deeper models and shorter training for simpler ones.

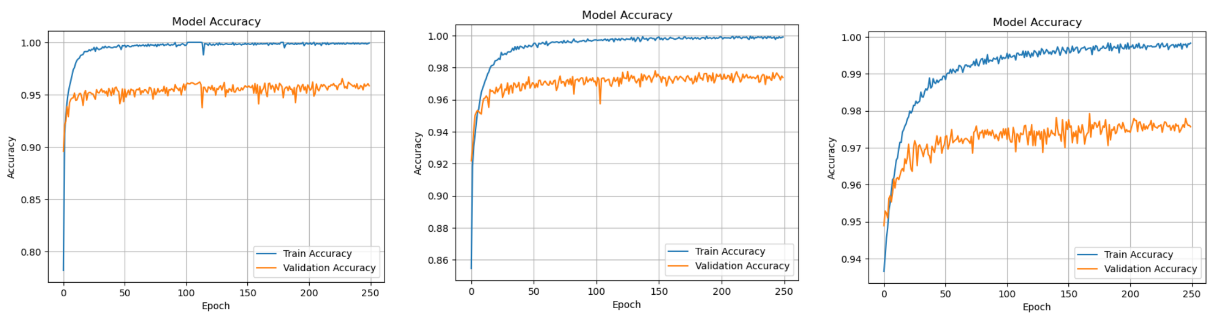
D. Performance of public BTM Dataset

1. **1D CNN** : The 1D CNN model showed significant improvement on the public BTM Dataset, achieving an accuracy of **99.45%,** precision of **99.19%,** recall of **99.69%,** and an F1-score of **99.44%.** This model demonstrated exceptional recall performance, which is crucial for high-quality classification.



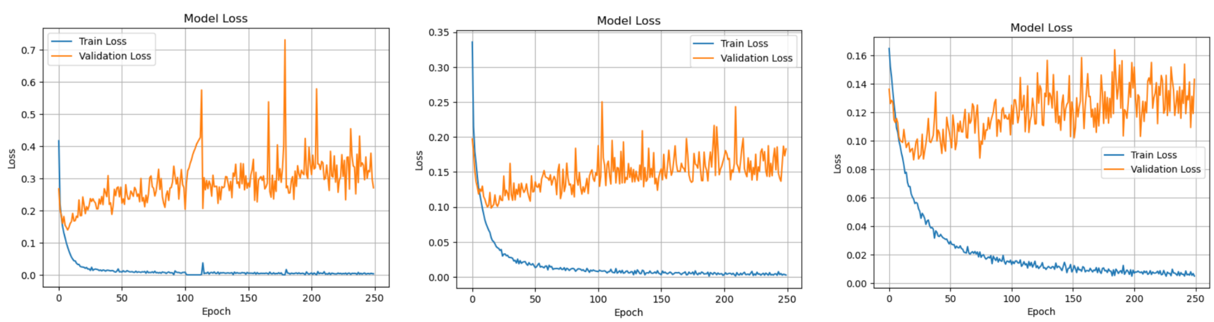
(a) 1D CNN (b) FCNN (c) DFN

FIGURE 4: Confusion Matrices of Classifiers using Newly Created MMCBT Dataset.



(a) CNN (b) FCNN (c) DFN

FIGURE 5: Training and Validation Accuracy Plots using Newly Created MMCBT Dataset.



(a) 1D CNN (b) FCNN (c) DFN

FIGURE 6: Training and Validation Loss Plots using Newly Created MMCBT Dataset.

2. **FCNN**: The FCNN classifier reached an accuracy of **99.65%,** precision of **99.80%,** recall of **99.49%,** and F1-score of **99.64%.** This model excelled in precision, while maintaining a very high recall and F1-score.
3. **DFN**: The DFN classifier achieved the best performance across all metrics on the public BTM Dataset as shown in Table 2, with an accuracy of **99.80%,** precision of **99.80%,** recall of **99.80%,** and an F1-score of **99.80%.** The DFN model delivered perfect balance across all performance metrics, resulting in the highest overall classification performance.

Figure 9 and Figure 10 describe the training and validation accuracy and loss. In CNN model, It achieved 100% training accuracy and 99.45% validation accuracy, where at the same time the training loss 8.47e-06% is and validation loss is 6.92%. In FCNN model, it achieved 99.93% training accuracy and 99.65% validation accuracy, where at the same time the training loss 0. 26% is and validation loss is 2.59%. In DFN model also describe the training and

TABLE 3: Comparison of Performance in terms of Accuracy between Proposed Method and Existing Work on Brain Tumor Detection

Author(s)	Classifier	Accuracy (%)
Mahesh Swami et al.(2020) [38]	k-means clustering	87.50
Mircea Gurbin et al.(2019) [39]	SVM	92.00
Tomasila, G. et al.(2020) [40]	RBF NN, DNN	83.00
Sakshi Ahuja et al.(2020) [35]	CNN, AlexNet	93.30
Shraddha S. More et al.(2021) [37]	NN, CNN	89.00
Manikandan Ramachandran et al. (2023) [41]	SVM	90.00
Hein Tun Zaw et al. (2019) [28]	Naïve Bayes	94.00
Khizar Abbas et al. (2019) [4]	LIPC	95.00
Arashdeep Kaur (2016) [3]	Fuzzy c-means	90.57
Sanjay Kumar C K et al.(2020) [26]	SVM	95.00
	1D CNN	95.85%
Proposed	FCNN	97.44%
	DFN	97.57%

TABLE 4: Model Accuracy and Timing Metrics of Newly Created MMCBT Dataset

Model	Accuracy (%)	Time/Epoch (s)	Test Time/Image (ms)
VGG16	96.55	1541	377
ResNet50	96.77	1623	700
CNN-2D	97.15	1429	197
DenseNet121	89.14	1390	1300
CNN-1D	95.85	45	178
FCNN	97.44	7	184
DFN	97.57	8	193

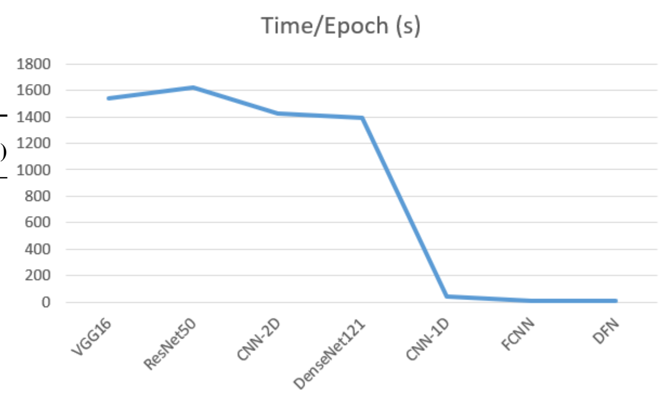


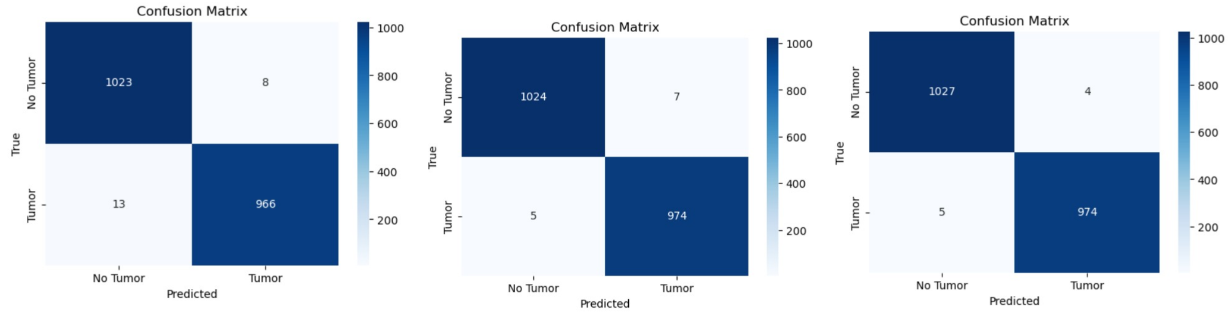
FIGURE 7: Comparison of Training Time of Different Algorithms using Newly Created MMCBT Dataset.

TABLE 5: Performance of public BTM Dataset

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
1D CNN	99.45	99.19	99.69	99.44
FCNN	99.65	99.80	99.49	99.64
DFN	99.80	99.80	99.80	99.80

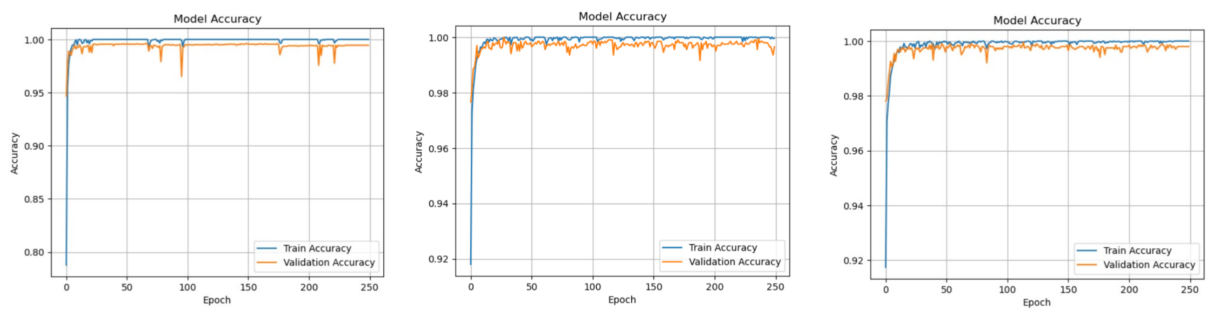
validation accuracy and loss of CNN. It achieved 100% training accuracy and 99.80% validation accuracy, where at the same time the training loss 0.0002% is and validation loss is 14.34%.

The Table 6 presents several research efforts along with their corresponding classification models and the accuracy they achieved. It includes multiple studies conducted by various authors who applied different machine learning methods to classification tasks. Each entry lists the author names along with the classifiers used and the accuracy results. The research incorporates a range of classifiers,



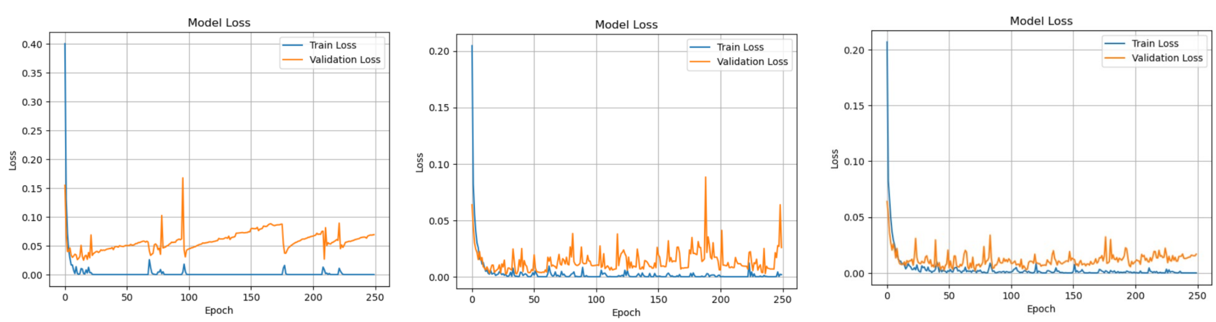
(a) 1D CNN (b) 1D CNN (c) 1D CNN

FIGURE 8: Confusion Matrices of Classifiers using public BTM Dataset.



(a) 1D CNN (b) FCNN (c) DFN

FIGURE 9: Training and Validation Accuracy Plots using public BTM Dataset.



(a) 1D CNN (b) FCNN (c) DFN

FIGURE 10: Training and Validation Loss Plots using public BTM Dataset.

including k-means clustering, SVM, RBF Neural Networks (NN), Deep Neural Networks (DNN), Convolutional Neural Networks (CNN), AlexNet, Naïve Bayes, LIPC, fuzzy c-means, and other modern techniques such as 1D CNN, Fully Convolutional Neural Networks (FCNN), and Deep Feature Networks (DFN). The classifiers achieved accuracy rates between 83% and 97.5%, with the highest performance recorded by the proposed models: 1D CNN at 95.85% and DFN at 97.5%

Figure 11 shows the training time per epoch is much less. For deep models, the ResNet-50 model has the longest training time, at 712 seconds, followed by the VGG16 model of 517 seconds. CNN-2D and DenseNet121 also exhibit similarly medium-length training times, at 494 seconds and 483 seconds, respectively. Compared to the CNN-2D model, the CNN-1D model is much faster, with each epoch requiring only 15 seconds. The quickest results are achieved with FCNN and DFN, needing only 3 seconds per epoch.

TABLE 6: Comparison of Performance in Terms of Accuracy between Proposed Method and Existing Work on public BTM Dataset

Authors	Feature Extraction Method	Classifier	Accuracy (%)
Pattabirama Mohan et al.(2024). [42]	SWT and GLCM	MobileNet	93.33
Md. Zakir Hossain Zamil et al. (2025) [43]	Convolutional Layer	CNN	94.28
Md. Ashraful Sharker Nirob et al. (2025) [44]	NM	DenseNet201, InceptionV3, MobileNetV3	87.21 / 82.30 / 92.01
Sayed Masuma Ali et al. (2025) [45]	FFV	Random Forest	97.00
		CNN	99.45%
Proposed	Pre-trained CNN, GAP, Linear Projection	FCNN	99.65%
		DFN	99.80%

TABLE 7: Model Accuracy and Timing Metrics of public BTM Dataset

Model	Accuracy (%)	Time/Epoch (s)	Test Time/Image (ms)
VGG16	99.72	517	326
ResNet50	99.69	652	689
CNN-2D	99.08	494	193
DenseNet121	97.75	483	1135
CNN-1D	99.45	15	169
FCNN	99.65	3	172
DFN	99.80	3	189

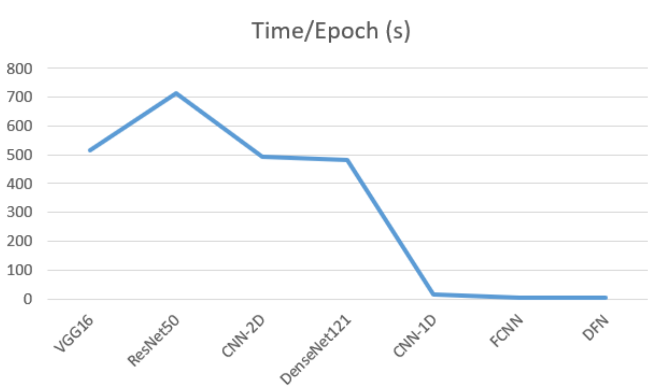


FIGURE 11: Comparison of Training Time of Different Algorithms using public BTM Dataset.

In Table 7 (public BTM Dataset), DFN stands out with the highest accuracy of 99.80%, along with extremely fast training (3 seconds per epoch) and test times (189 ms per image), making it the most efficient and balanced model. VGG16 follows closely with 99.72% accuracy, though it takes significantly longer for training (517 seconds per epoch) and testing (326 ms per image). CNN-2D and CNN-1D also perform well, with accuracies of 99.08% and 99.45%, respectively, but CNN-1D is notably faster in training (15 seconds per epoch) and testing (169 ms per image). FCNN offers 99.65% accuracy, with exceptionally fast training (3 seconds per epoch) and a test time of 172 ms per image, making it a strong contender for efficiency. DenseNet121, with the lowest accuracy of 97.75%, also has the slowest test time (1135 ms per image), making it less efficient than the other models.

The results indicate that the DFN classifier achieved the highest performance on both datasets. On the Newly Created Newly Created MMCBT Dataset, DFN achieved an accuracy of **97.57%,** while on the public BTM Dataset, it reached an accuracy of **99.80%,** with a perfectly balanced performance across all metrics. FCNN also performed exceptionally well, particularly in terms of recall, while 1D CNN demonstrated solid results but with slightly lower performance in comparison.

These findings demonstrate that the DFN classifier, particularly when combined with feature extraction techniques like ResNet50, GAP, and Linear Projection, offers robust and consistent performance across different datasets.

VI. Conclusion

In this paper, we proposed an automatic and efficient deep-learning framework for brain tumor detection from MRI scans. The approach leverages a pre-trained ResNet50 model for feature extraction, enhanced by Global Average Pooling (GAP) and linear projection to generate compact and discriminative image representations. A novel Dense-Dropout sequence was introduced to improve non-linear feature learning, reduce overfitting, and enhance model robustness. A key contribution of this work is the development of the Mymensingh Medical College Brain Tumor (MMCBT) dataset, which provides a clinically verified and balanced resource comprising 209 subjects and over 16,000 MRI images. This dataset addresses the scarcity of reliable brain tumor MRI data and establishes a strong foundation for future research in automated diagnosis. Extensive experiments conducted on both the MMCBT dataset and the publicly available BTM dataset demonstrated the effectiveness of the proposed framework, achieving accuracies of 97.57% and 99.80%, respectively, along with strong precision, recall, and F1-scores. These results underscore the potential of our approach as a robust and reliable tool for clinical decision support. The proposed framework combines methodological innovation with valuable dataset creation, significantly advancing research on brain tumor detection. While some limitations remain, this work contributes a step forward toward the development of automated diagnostic systems capable of assisting radiologists, improving diagnostic efficiency, and ultimately supporting better patient outcomes.

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