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Deep Neural Network-Based Detection of Brain Tumors Using MRI Images

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***Abstract*—Brain tumors constitute the most dangerous type of neurological disorder, where delayed or incorrect diagnoses may significantly affect patient survival chances. Owing to the fast development of artificial intelligence, Machine learning (ML) and Deep Learning (DL) approaches along with the Magnetic Resonance Imaging (MRI) method proved to be efficient solutions for brain tumor detection and classification. This research paper presents the novel DNN-based method for precise detection of brain tumors based on MRI images of the BraTS 2020 dataset. In total, 2,892 MRI images were used for the training of the model, which included T1-weighted, T2-weighted, and FLAIR modalities. The preprocessing of the images included data cleaning, resizing, augmentation, one-hot encoding, and Z-score normalization of the images to increase their quality and model generalization. The information set was divided into 70:20:10 training, validation, and testing sets. The proposed DNN framework could learn discriminative tumor features and demonstrated better classification results than CNN, FCN, ResNet50, and InceptionNet models. As a result, the proposed DNN provided the following values: Accuracy (ACC) - 99.80%, Precision (PRE) - 99.85%, Recall (REC) - 99.84% and F1-Score (F1) - 99.81%. These findings Demonstrate the efficacy and dependability of the devised method, which holds tremendous potential as a trustworthy computer-aided diagnostic tool for brain tumour diagnosis.**

Keywords*—*Brain Tumor Classification, Magnetic Resonance Imaging, Deep Learning, Artificial Hummingbird Algorithm, Medical Image Analysis.

I. Introduction

The early and accurate diagnosis of diseases is essential in modern medicine because it leads to timely treatment [1], Improving survival rates, and assisting with clinical decision-making and management of diseases [2]. Because they impact the central nervous system, brain tumours are among the most deadly neurological disorders and a major threat to human health. The main functions of life, including thought, making decisions, feeling, and motion, are controlled by the brain and spinal cord [3]. Abnormal cell proliferation in the brain causes brain tumours, which can be classified as either main tumours [4][5], Brain tumours can be classified as being either primary, meaning they start in the central nervous system, or secondarily, meaning they spread from other parts of the human body to the brain. Brain Tumors, according to health statistics globally, cause many cases of sickness and death associated with cancers; hence the importance of diagnosis [6].

MRI is among the usually employed medical diagnostic imagination procedures in analyzing brain tumors due to the excellent soft-tissue distinction and high spatial resolution. MRI imaging technology helps visualize brain structures non-invasively and aid physicians in detecting any anomalies like tumors, edema, and lesions [7][8]. Image processing methodologies for medical images, especially image segmentation and image classification methods, have an important role in obtaining medically significant data from MRI images. Proper image segmentation provides important information about tumor position, size, and form [9]. However, interpreting MRI images manually is both a time-consuming process highly reliant on the skills of radiologist, which renders the entire process vulnerable to variability and human error [10][11][12].

In order to solve the problems mentioned above, computer aided diagnostic methods have attracted much attention recently. In this regasrd, ML and DL have been widely used in noticing and ordering brain tumors from MR images [13][14][15]. While conventional ML-based methods mostly rely on manually engineered feature extraction and selection processes prior to classification, DL algorithms learn feature hierarchies automatically from medical images. Despite successful results of the intelligent algorithms in discriminating between tumor and non-tumor tissues, classical ML-based methods face difficulties in recognizing spatial and structural features inherent to MRIs [16][17][18].

A. Motivation and Contribution

Motivation for the current study comes about due to the rising number and intensity of brain tumors, which necessitate proper diagnosis in order to ensure successful behavior and existence of the patient. Manually diagnosing brain tumors using MRI is not only time consuming but is also individual and prone to errors. There have been efforts made to employ the use of ML and DL algorithms in order to come up with automatic computer aided diagnosis systems. Thus, this research aims at designing an effective model based on Deep Neural Networks. Contributions of this research include:

- Aims to create an efficient DNN approach for diagnosing brain tumors from MRI images.
- Utilizes the BraTS 2020 dataset for robust model training and evaluation.

- uses sophisticated preprocessing methods that boost information quality, such as enhancement, normalization, and data cleaning.
- Achieves high classification performance with superior ACC, PRE, REC, and F1.
- Outperforms existing models such as CNN, FCN, ResNet50, and InceptionNet.
- Supports accurate and reliable brain tumor diagnosis for clinical decision-making and healthcare applications.

The **justification** of this study lies in critical need for early, accurate, and automated brain tumor detection to support clinical decision-making and reduce diagnostic errors in MRI analysis. Physical clarification of MRI scans is time-consuming and highly dependent on radiologist expertise, which may lead to variability in results. To address these limitations, the proposed work introduces a Deep Neural Network (DNN)-based framework that effectively learns complex tumor-related features from multi-modal MRI images in the BraTS 2020 dataset. The novelty of this approach lies in its optimized preprocessing pipeline combined with a simplified yet highly effective DNN architecture that achieves superior performance compared to existing models such as CNN, FCN, ResNet50, and InceptionNet. The proposed method demonstrates exceptional ACC and robustness, making it a reliable and efficient solution for automated brain tumor detection and advancing AI-driven medical imaging systems.

B. *Organization of the Paper*

The remainder of the document is organized as follows: The pertinent study on brain tumour identification is described in Section II. Section III provides an outline of the suggested technique. The performance of the suggested approach is compared with other existing approaches listed in Section IV using the simulated setup and assessment matrices. A conclusion with future research goals is provided in Section V.

II. Literature Review

A comprehensive review and analysis of key research studies on Brain Tumors Detection was conducted to inform and enhance the development of this study.

Selvan et al. (2025) Describes an easy-to-use, multi-phase system that helps physicians detect brain tumors earlier and more accurately by integrating patient symptoms with CT and MRI imaging data. A rule-based symptom analyzer recommends a CT scan if symptoms persist beyond 7 days. Deep learning models analyze CT and MRI scans with accuracies exceeding 96% and 97%, respectively. In positive cases, a segmentation model identifies the tumor region, estimates its size, and grades severity. Heatmaps enhance interpretability, while combining CT and MRI results improves sensitivity and reduces false positives for more reliable diagnosis [19].

Yadav and Upadhyay (2024) seeks to investigate how cutting-edge ML approaches enhance brain tumour identification and facilitate precise diagnosis and treatment planning using MRI images. The study compares the detection techniques and ACC of many ML and DL systems. The suggested approach preprocesses a Kaggle dataset and uses a DCCN model to identify and categorise four different kinds of brain tumours. It also emphasizes model interpretability, clinician trust, and future research directions such as cross-hospital knowledge sharing and multimodal data integration. The proposed system achieves an ACC of 97.24% [20].

Kale, Gadicha and Dalvi (2024) provide a variety of DL and ML methods for the quick and precise identification and categorisation of brain tumours from MRI pictures. Before assessing many models, including LR, SVC, kNN, NB, NN, RF, and K-means clustering, the study uses preprocessing and data augmentation techniques. ACC, PRE, REC, F1, and AUC were used to evaluate performance. Among the assessed models, LR and RF attained 96% ACC, while NN attained 95%. These models showed a great capacity to differentiate tumour from non-tumor pictures and produce trustworthy diagnostic outcomes [21].

Tang and Teoh (2023) seeks to use DL techniques to solve the problem of accurate brain tumour identification. This work examines the use of the pre-trained ResNet18 model for brain tumour identification from MRI scans, but a number of models, including as GoogLeNet and CapsNet, have been investigated. With an ACC of 88.33%, sensitivity of 86.67%, specificity of 90.00%, and PRE of 89.66%, the model demonstrated successful tumour identification performance when tested on a publicly accessible Kaggle dataset [22].

Jansi et al. (2023) suggests a thorough framework for brain tumour diagnosis that makes use of convolutional neural networks (CNNs), data augmentation, and picture preparation. This study utilizes multimodal MRI images from the BRATS dataset, enhanced through preprocessing, dilation, and erosion to improve tumor visibility. A CNN model is trained using shuffled data to enhance performance, with implementation carried out using TensorFlow and Keras. The proposed framework achieved an ACC of 98.2% in brain tumor detection, demonstrating its potential to assist healthcare professionals in accurately identifying brain tumors [23].

Shetty et al. (2022) A binary classifier was created in the proposed study to identify brain tumours based on MRI. This study discusses the use of a convolutional neural network and a ML model for MRI-based brain tumour diagnosis. This study made use of an available dataset. There are 1500 brain MRI pictures with tumours and 1500 brain MRI pictures without tumours in the collection. The results show that the CNN model outdid the ML methods with an ACC of 98.21% [24].

The table I provides an overview of recent research on Brain Tumors Detection, detailing the proposed models, utilized datasets, major findings, and encountered challenges.

TABLE I. Recent Studies on Brain Tumors Detection using Machine Learning technqiues

Author	Proposed Work	Dataset	Findings	Limitations & Future Work
Selvan et al. (2025)	Developed a multi-phase system integrating symptom analysis, CT scan detection, MRI classification, and tumor segmentation for early diagnosis.	CT and MRI brain scan datasets	Achieved >96% accuracy for CT-based detection and >97% accuracy for MRI-based classification.	Limited evaluation on diverse clinical datasets; future work may focus on real-time deployment and larger multi-center validation.

Yadav and Upadhyay (2024)	Applied Deep Convolutional Neural Network (DCCN) for four-class tumor detection after preprocessing MRI images.	Kaggle Brain Tumor Dataset	Achieved 97.24% accuracy.	Requires improved interpretability and multi-modal data integration for enhanced diagnosis.
Kale, Gadicha and Dalvi (2024)	Compared multiple ML models including LR, SVC, kNN, NB, NN, RF, and K-Means for MRI classification.	MRI Brain Tumor Dataset	LR and RF achieved 96% accuracy, while NN achieved 95%.	Future studies may investigate deep learning architectures for improved performance.
Tang and Teoh (2023)	Proposed ResNet18-based deep learning model for MRI tumor detection.	Kaggle Brain MRI Dataset	Accuracy: 88.33%, Sensitivity: 86.67%, Specificity: 90%, Precision: 89.66%.	Performance can be enhanced through transfer learning and larger training datasets.
Jansi et al. (2023)	Combined preprocessing, augmentation, dilation, erosion, and CNN for tumor detection.	BraTS Brain Tumor Dataset	Achieved 98.2% accuracy.	Further improvements are possible through advanced feature extraction and optimization methods.
Shetty et al. (2022)	Developed CNN and ML-based binary classifier for tumor and non-tumor MRI images.	3,000 MRI images (1,500 tumor and 1,500 non-tumor)	CNN achieved 98.21% accuracy.	Limited to binary classification; future work may focus on multi-class tumor categorization.

Research gaps: Despite significant advancements in ML and DL methods for brain tumor detection using MRI images, several challenges remain unresolved. Existing studies often have small sample sizes, binary classification methods, poor generalization ability, and require complex preprocessing or segmentation methods. In addition, some of the models have limited validation in large-scale clinical environment, limited interpretability, or lower ACC. Therefore, there is a need for a robust and highly accurate deep learning framework capable of effectively learning complex tumor features from multi-modal MRI images while providing reliable and consistent performance. By creating a DL based framework for identifying brain tumours in MRI images, this project seeks to address these issues and provide more precise classification findings, dependable diagnostic outcomes, and efficient clinical decision-making.

III. Research Methodology

In this study, the BraTS 2020 dataset comprising 2,892 MRI images (T1, T2, and FLAIR modalities) was utilized for brain tumor detection. The MRI images were processed by cleaning, resizing, augmenting, one-hot encoding, and Z-score normalizing the data, and subsequently dividing it into train, authentication, and test sets (70:20:10). A Deep Neural Network (DNN) model with fully linked layers and ReLU beginning was developed to learn tumor-related features and perform classification. Model Performance evaluation was carried out using confusion matrices and also by employing traditional methods for evaluation like ACC, PRE, REC, and F1 to measure the efficiency of detection. Fig. 1 gives a presentation of the proposed flow chart of Brain Tumor Discovery Using MRI Images using ML.

The below section highlights the description of all stages of the proposed methodology:

A. Data Gathering and Analysis

The experiments were performed using the BraTS 2020 dataset. There were 2,892 MRI images, which include T1, T2, and FLAIR modalities, that were analyzed in order to detect brain tumors. There are images with various tumor properties and anatomical features in the dataset that allow efficient model training and testing. Data visualization methods like bar plot and heatmap were used for analyzing the distribution of data, class balance, and correlation of features, as follows:

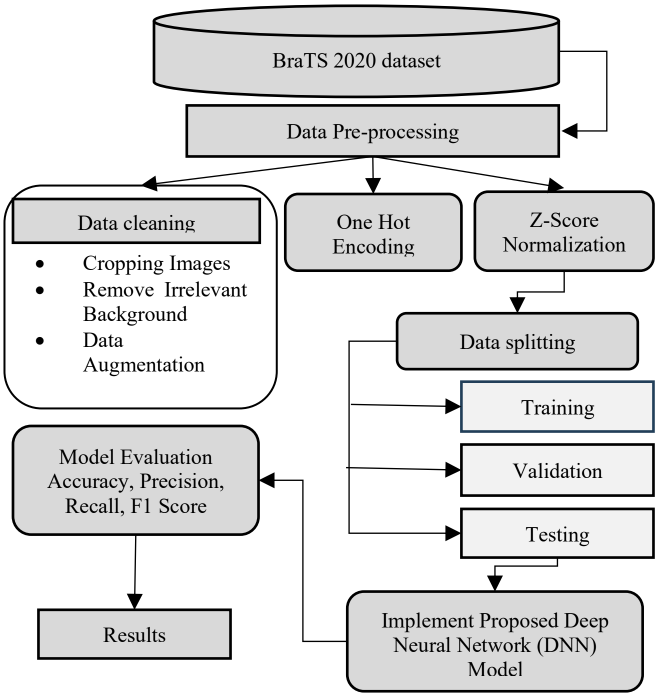

Fig. 1. Proposed flowchart for Brain Tumors Detection Using MRI Images using machine learning

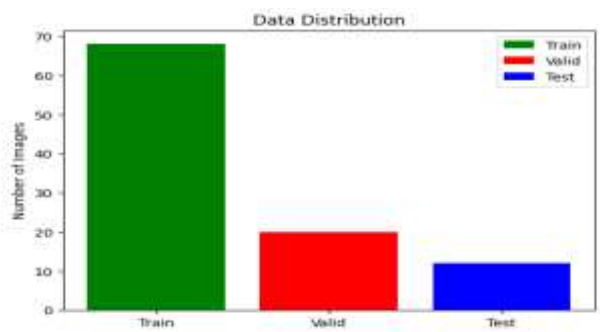

Fig. 2. Bar graph of class distribution

Figure 2 shows the distribution of the MRI images utilized in brain tumor classification among the exercise, authentication, and challenging datasets. Exercise dataset comprises the highest number of images to allow proper learning, whereas authentication and difficult datasets are meant for fine-tuning and assessing the performance of the suggested model, respectively.

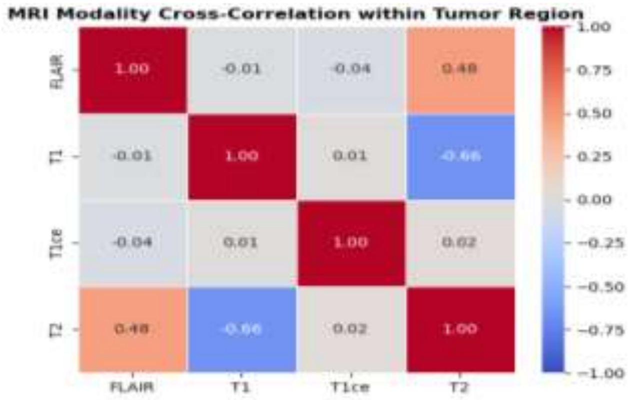

Fig. 3. Heatmap of MRI Modalities Correlation within the Tumor Area

Figure 3 shows the heatmap of correlation among different MRI modalities within the tumor area. The findings show that there is a relatively high positive correlation between FLAIR and T2 images (0.48), indicating that the two contain similar information about the tumors, while the other pair has a highly negative correlation of -0.66. The rest have little to no correlation, emphasizing the complementary role of MRI modalities in brain tumor diagnosis.

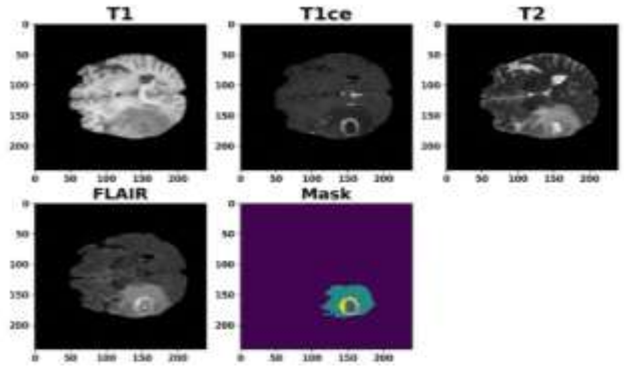

Fig. 4. Comparison of Structural MRI Modalities and Ground-Truth Segmentation Mask for Brain Tumor Identification

Figure 4 demonstrates the multi-modal MRI scans from the BraTS dataset, which include T1, T1ce, T2, and FLAIR along with the ground-truth division mask. The subdivision mask is used to indicate the accurate tumor area and edema zone of the tumor. Each modality highlights different aspects of the brain anatomy and tumor. This visualization demonstrates the combination of several MRI modalities to detect and segment brain tumors successfully.

B. *Data Pre-processing*

The statistics training phase was done using BraTS 2020 Dataset to make sure that high quality of input data is achieved for brain tumor identification. The preprocessing phase comprised of the following activities – image rescaling and normalization, data augmentation, and labeling of MRIs. The major preprocessing methods applied in the current research are briefly described below:

C. *Data cleaning*

Steps for data cleaning were taken to increase the value and reliability of the MRI scans of the BraTS 2020 data set. Preprocessing steps included cropping images to remove unwanted parts of the background and keeping only the relevant part containing the brain and the tumor, and then resizing the images to have a fixed size for effective calculations and feeding into the machine learning models. Data augmentation steps like rotation, translation, shearing, flipping, and brightness changes were done to create training samples that can help to avoid overfitting.

D. *One Hot Encoding*

The one-hot encoding technique is used to encode the labels for these sub-classes. A value is assigned to each sub-class, and the encoder is updated based on this assignment.

E. *Z-Score Normalization*

Data normalization is the procedure of changing or standardizing data to have a similar pattern. The most popular method for data normalization is scaling up, often referred to as z-score normalization and min-max normalization. This study employed Z-score normalizations, a standardization technique with a mean of 0 and a standard deviation of 1. This scaling technique adjusts the values cantered about the typical value using a unit standard deviation. The z-score normalization is specified by Equation (1).

$$E' = \frac{E-\bar{M}}{\sigma_M} \quad (1)$$

Where,

E' and E are new and old for each data entry, $\bar{M}$is the mean, and σ_M is the normal nonconformity.

F. *Data Splitting*

The collection of data was divided into training, validation, and testing sets using a stratified split ratio of 70:20:10. A stratified sampling approach was utilised to maintain the original class distribution across all subsets in order to guarantee that each subset accurately represented the characteristics of the full dataset and to enable reliable modelling, verification, and evaluation.

G. *Proposed Deep Neural Network (DNN) Model*

A Deep Neural Network (DNN) model for accurate MRI image-based brain tumour identification is proposed in this research. The deep neural network (DNN) is one popular DL technique among scholars. The DNN's network structure consists of the input, hidden, and output layers, all of which are fully connected. Each neurone is connected to every other neurone in the layer above it, but it is not connected to any neurones in the layers below. An activation function that operates on the output after each network layer strengthens the effects exhibited by network training. Consequently, DNN may also be viewed as a massive perceptron composed of several sensory neurones. The ith layer forward propagation computation formula is as follows (2):

$$x_{i+1} = \sigma(\sum w_i x_i + b) \quad (2)$$

where x stands for the parameter value, w for the weight factor matrices, and b for the bias vector. In an unified class a network, ReLU is commonly used as a function of activity; the formula is as follows(3):

$$\sigma(x) = max(0, x) \quad (3)$$

In order to optimize the system configuration, the cost functions compute the backpropagation of the network by measuring the output loss of trained samples. Cross-entropy is typically selected as the loss parameter in the coding job; the formula is as follows (4):

$$C = -\frac{1}{N}\sum_x \sum_{i=1}^{M}(y_i log p_i) \quad (4)$$

where N represents the size of the input data set, M the number of categories, yi if the grouping i corresponds to the real category, and pi the probability of falling into category i. The proposed Deep Neural Network (DNN) model was trained using the Adam optimizers with a training rate of 0.001 for ten epochs, a batch size of 32, and an input image size of 240 × 240 pixels. With ReLU activation in the hidden layers and Softmax activation in the output layer, the network employed categorical cross-entropy as the loss function. A dropout rate of 0.5 was employed throughout training sessions in order to improve generalization and lessen excess overfitting.

H. Evaluation metrics

The recital of the above-mentioned DNN-based model was assessed based on a set of classification estimation metrics. The confusion matrix was created to determine TP, FP, TN and FN of the model predictions. On their basis, ACC, PRE, REC and F1 metrics determined to evaluate the effectiveness of brain tumor recognition:

Accuracy: ACC refers to the percentage of exactly confidential cases against the entire number of cases in the database. This measure assesses the effectiveness of the classifier as it tells us about the number of cases that were classified correctly. It is computed from equation (5)-

$$Accuracy = \frac{\text{TP+TN}}{\text{TP+Fp+TN+FN}} \tag{5}$$

Precision: PRE is proportion of correctly predicted confident explanations over the entire quantity of instances forecast as positive. PRE gauges effectiveness of the classification algorithm in making accurate positive predictions and is defined by Equation (6)-

$$Precision = \frac{\text{TP}}{\text{TP+FP}} \tag{6}$$

Recall: REC is fraction of true positives among the actual positives in the data set. It is the measure of the effectiveness of a classification model to find all the relevant positives and is represented by Equation (7)

$$Recall = \frac{\text{TP}}{TP+FN} \tag{7}$$

F1 score: The F1 is the vocal mean of the PRE and REC, balancing both criteria. It has a value between 0 and 1, with larger numbers being better, and is computed by Equation (8)-

$$F1 - score = 2 \times \frac{Precision \times Recall}{Precision + Recall} \tag{8}$$

IV. Results And Discussion

The experiment's specifics and the assessment of suggested model during training and testing have been covered in this part. The outcomes demonstrate the efficacy of the suggested approach and its successful calculation for a precise categorization outcome.

A. Experimental Setup

In this research, have implemented the proposed model using the Python programming language. Here, the TensorFlow library, an open-source Deep Learning library of Python, has been utilized for implementation of the model. The experiment was conducted using a 64 bit CPU and RTX 3090 GPU of Windows operating system having Core i9 of 10th generation processor.

B. Experimental Results

Table II presents the categorizing result of the suggested DNN-based model on MRI brain tumour information employing the BraTS 2020 collection. The model performed with 99.80% ACC, PRE, REC, and F1, showing that it possesses excellent capabilities in correctly classifying MRI images. The derived values' stability across all assessment measures demonstrates how accurately and dependably the suggested model operates.

TABLE II. CLASSIFICTION RESULTS OF PROPOSED MODEL BRAIN TUMORS DETECTION USING MRI IMAGES

Matrix	Testing	Training
Accuracy	99.80	100
Precision	99.85	100
Recall	99.84	100
F1-score	99.81	100

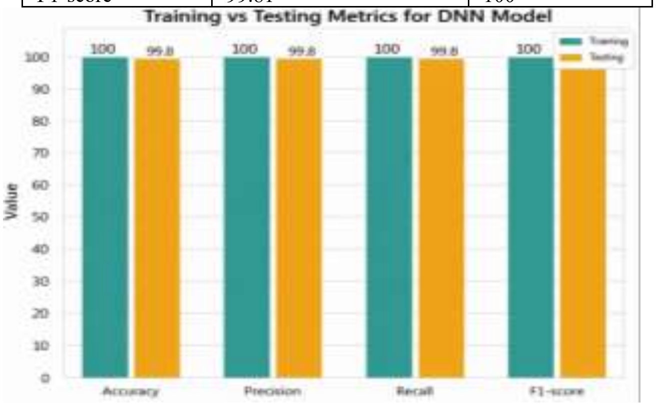

Fig. 5. Train and Test performance comparison of proposed model for Brain Tumors Detection

The suggested DNN model for brain tumour detection's training and testing performance metrics are compared in Fig. 5. On the training dataset, the model obtained 100% ACC, PRE, REC, and F1; on the experimental dataset, all assessment metrics were 99.80%. The model's outstanding generalization power and resilience are demonstrated by the little difference between training and testing results, suggesting that it can reliably identify and classify brain tumours without suffering from major overfitting.

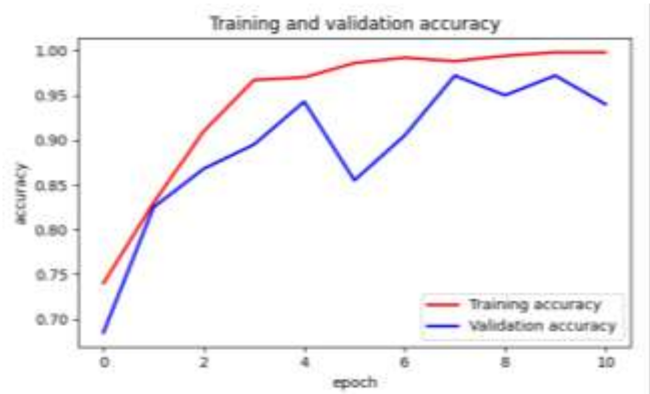

Fig. 6. Accuracy Curve for proposed DNN model

Fig. 6 shows the suggested DNN model's training and validation ACC curves over the training phase. As the quantity of epochs rises, both charts consistently demonstrate an enhancement in ACC, demonstrating successful feature extraction and model optimization. The validation ACC closely follows the training ACC throughout the training period, demonstrating good generalization capability and stable performance on unseen data. The model successfully avoids overfitting and delivers reliable results for brain tumour diagnosis and classification, as seen by the narrow gap among both of the lines.

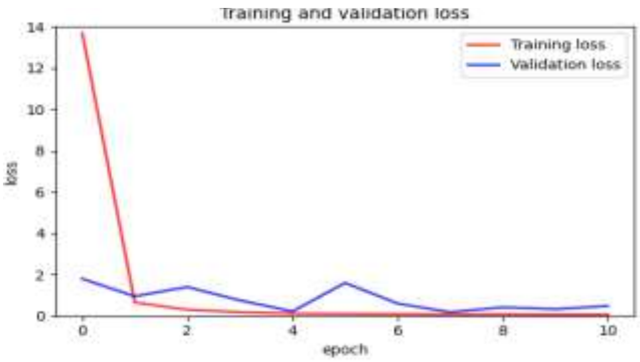

Fig. 7. Loss Curve for DNN model

Fig. 7 shows exercise and authentication loss curves of proposed DNN model with varying number of epochs. The exercise loss reductions abruptly during the initial epochs and gradually stabilizes at a very low value, indicating effective learning and junction of the model. Additionally, confirmation loss exhibits a generally declining trend with slight variations, indicating the model's strong generalizations on unobserved data. The consistently low loss values and the close relationship between the exercise and authentication curves demonstrate stable training performance, reduced prediction errors, and minimal overfitting in brain tumor discovery and classification.

C. Comparative analysis

Table III presents a comparison analysis of the suggested Deep Neural Network (DNN) model with various current approaches in order to determine its efficacy. The comparison includes Convolutional Neural Network (CNN), Residual Network-50 (ResNet50), Fully Convolutional Network (FCN), and Inception Network (InceptionNet). The proposed DNN achieved the highest performance with 99.80% ACC, PRE, REC, and F1, outperforming InceptionNet, which obtained 98.55% ACC, and CNN, which achieved 86.1% ACC. These results clearly demonstrate the superior classification capability, robustness, and reliability of the proposed DNN model for MRI image classification.

TABLE III. COMPARISON OF DIFFERENT MACHINE LEARNING MODELS FOR BRAIN TUMORS DETECTION USING MRI IMAGES

Model	Accuracy	Precision	Recall	F1-score
CNN[25]	86.1	81.6	76.69	91.58
ResNet50 [26]	93.31	35.77	35.89	35.83
FCN[27]	78.9	81.4	72.56	-
InceptionNet[27]	98.55	96.83	98.50	97.65
DNN	99.80	99.85	99.84	99.81

D. Discussion

The proposed Deep Neural Network (DNN) demonstrated outstanding performance, achieving 99.80% ACC and significantly outperforming the compared ML and DL models. The high ACC, PRE, REC, and F1 indicate the model's strong capability to learn complex patterns from MRI images and make highly reliable classifications with minimal errors. The integration of optimized feature extraction and effective learning mechanisms enabled the DNN to achieve superior generalization and robustness. These findings demonstrate that the suggested DNN is a reliable and efficient method for organizing MRI images, making it appropriate for practical standard MRI analysis purposes.

V. CONCLUSION AND FUTURE STUDY

A brain tumour is the growth of abnormal brain cells, some of which can lead to cancer. Brain tumours are usually detected by magnetic resonance imaging (MRI) scans. The MRI images provide details on the abnormal tissue growth in the brain. This study proposed a Deep Neural Network (DNN)-based approach for brain tumour identification using MRI images from the BraTS 2020 collection. The MRI data were preprocessed through data cleaning, augmentation, one-hot encoding, and Z-score normalization to enhance data quality and improve model performance. According to empirical results, the suggested DNN model outperformed CNN (86.1%), FCN (78.9%), ResNet50 (93.31%), and InceptionNet (98.55%) with an ACC of 99.80%. These results demonstrate how well the DNN model extracts intricate cancer-related information and correctly identifies brain tumours, making it a dependable computer-aided diagnostic tool for clinical judgement and prompt identification.

A. Study Limitations and Future Work

Although the proposed DNN model achieved high ACC in brain tumor discovery, the study has certain limits. The model was tested exclusively for the BraTS 2020 dataset, and might not be generalizable to other clinical datasets and real-life healthcare environment. Additionally, the study focused primarily on tumor classification and did not address tumor segmentation, grading, or explainable AI techniques. Further research can aim to validate the model with more extensive multi-center datasets, incorporate more sophisticated deep learning architectures and attention mechanisms, develop explainable AI techniques for increased interpretability and clinical applicability, and explore the potential of real-world applications.

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