International Journal on Perceptive and Cognitive Computing (IJPCC) Vol 11, Issue 1 (2025)
https://doi.org/10.31436/ijpcc.v11i1.510

A Study on the Classification of Brain MRI Images for Brain Tumor Detection

A Comparative Analysis

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(Received: 10th December 2024; Accepted: 27th December, 2024; Published on-line: 30th January, 2025)

Abstract**—** Accurate classification of brain tumors is essential for effective diagnosis, as it directly affects treatment choices, patient outcomes, and survival rates. Early and precise detection enables timely interventions, reducing the risk of tumor progression. Without reliable classifiers, traditional feature extraction techniques have drawbacks. Our study suggests a hybrid model that incorporates the advantages of Random Forest Classifier (RFC), Support Vector Machine (SVM), and Visual Geometry Group (VGG16) to improve classification performance. To improve feature extraction, the Magnetic resonance imaging (MRI) images are pre-processed. This includes pixel intensity. To improve data diversity, augmentation techniques such as random flip, random height, random width, horizontal flip, and vertical flip are used. Next, a unique Deep Convolutional Neural Networks (DCNN) that is VGG16 is created to extract significant deep features. Evaluation of the model's performance using various optimizers revealed that the RMSprop optimizer outperformed models employing Adam (80.39%) and SGD (64.71%), achieving the highest validation accuracy (82.35%). SVM obtained a validation accuracy of 47.06%, while RFC obtained 64.71%. These results show the importance of classifier and optimizer selection. This study highlights the efficacy of the VGG16 model with the RMSprop optimizer and shows the potential of integrating deep learning and conventional machine learning approaches for brain tumor classification. It demonstrates the potential of combining deep learning and traditional machine learning techniques for brain tumor classification, highlighting effectiveness of the VGG16 model with the RMSprop optimizer while emphasizing the need for further exploration of optimizers and classifiers to enhance overall model performance and robustness.

Keywords— Brain tumor, MRI scan, Deep learning, Optimizer, Classifier

I. Introduction

The rapid growth in technology has been drastically changing the arena of medical science and, simultaneously, impelling a profound effect on the technique of diagnosis. Deep learning combined with sophisticated computers made various innovative methods possible, especially in the field of medical imaging. The focus is on the critical task of brain tumor classification, utilizing the latest advancements in deep learning to enhance diagnostic accuracy; therefore, the contribution to this rapidly evolving field is significant.

Brain tumors represent an abnormal growths of brain tissue. There are over 120 diverse types of brain tumors, only some of which are malignant. Brain tumors, including malignant ones, accounted for 18,020 adult deaths in the US in 2020, making them the tenth most common cause of death [1]. The variety of tumor forms, such as pituitary tumors, meningiomas, and gliomas, highlights how difficult the situation is. Because brain tumors can quickly become life-threatening and require adequate therapy for patient survival, the importance of early diagnosis is emphasized. In this diagnostic process, medical imaging modalities like computed tomography (CT), magnetic resonance imaging (MRI), and X-rays have become essential tools. Image classification performance has greatly improved with the shift from human to machine-dependent processes, especially in computer-aided design (CAD) systems, where image classification performance now much exceeds that of manual detection.

This introduction sets the context by highlighting recent developments and trends in the field. It emphasizes the importance of technology advancements and their influence on medical knowledge, setting the stage for the study's specific focus on brain tumour classification. The study explores the complexities of feature extraction, post-processing, and preprocessing processes in the CAD system process. It uses methods like noise reduction, image smoothing, and scaling to maximize the input data because it understands how important image preprocessing is. Furthermore, it recognizes the vital role that post-processing methods in particular, segmentation procedures play in enabling the extraction of tumour areas from MRI data. The significance of feature extraction methods in obtaining appropriate features for later classification is emphasized throughout the paper.

The paper presents the most recent developments in deep learning while keeping an eye on the shortcomings of conventional machine learning classifiers. Deep learning, an acknowledged subfield of machine learning, enables computers to learn from data and make judgments. Deep learning is less reliant on preprocessing, which reduces the complexity involved in choosing segmentation processes, feature extraction processes, and classifiers. To improve brain tumor classification accuracy, the paper presents a unique hybrid strategy that combines a Support Vector Machine (SVM) classifier with a Deep Convolutional Neural Network (DCNN: VGG16) and a Random Forest Classifier (RFC) classifier with a Deep Convolutional Neural Network (DCNN: VGG16) for deep feature extraction. The hybrid structure's justification is to overcome the shortcomings of conventional approaches and maximize the core strengths of both deep learning and traditional machine learning classifiers. This provides the way for a comprehensive review of the research's details and highlights its innovative and important applications in the quickly developing field of medical image classification.

II. Literature Review

With the use of several artificial intelligence (AI) algorithms, the classification of brain tumors has advanced significantly. Magnetic Resonance (MR) image feature extraction and subsequent classification based on these retrieved characteristics are critical steps in this complex process. Researchers have worked hard to enhance the traditional classification techniques; below is a thorough rundown of some important studies in this area.

A "Figshare" dataset was used in the work of Biswas et al. [2]. Nevertheless, there were issues with their work, including low data volumes, expensive MRI processing, and decreased accuracy. Damodharan et al. utilized a neural network for brain tumor detection, integrating various classifiers, including Bayesian and K-Nearest Neighbors (KNN), along with multiple preprocessing techniques. Despite KNN achieving an accuracy of 83%, the study faced limitations due to the small dataset used, which affected the generalizability of the findings [3].

Abiwinanda et al. proposed a feature extraction and classification approach entirely based on Convolutional Neural Networks (CNNs) without any preprocessing stages. In their study, the softmax classification layer yielded poor performance despite achieving 84.19% accuracy on the dataset used, highlighting the effectiveness of the CNN-SVM model and the importance of incorporating preprocessing steps for improved results [4].

Khan et al. investigated the application of transfer learning for the classification of brain tumors, employing the VGG19 architecture, which resulted in an accuracy of 94.82%. However, they noted that transfer learning requires significant processing power and involves complex network structures [5].

Pashaei et al. achieved an accuracy of 93.68% by combining Convolutional Neural Networks (CNNs) for feature extraction with an extreme learning machine for classification. Notably, the proposed CNN architecture outperformed both RBF and SVM classifiers. Other experiments utilized different hybrid models, focusing on identifying the most effective feature extraction techniques [6].

Kurmi et al. utilized an MLP classifier, achieving an average accuracy of 91.76%. Their work focused on image enhancement, tumor area initialization, and region refinement, contributing to more effective brain tumor detection [7].

Mahesh and Yogesh proposed a Convolutional Neural Network (CNN)-based approach for brain tumour identification and classification that achieved 97.5% test accuracy across four classes: meningiomas, pituitary tumours, gliomas, and no tumour. Using a strong CNN architecture, their method successfully solved the drawbacks of previous research, which included issues like short datasets or insufficient preprocessing. The model's excellent accuracy and recall across all tumour classifications indicated its dependability and efficacy in supporting diagnosis.[8]

To classifying brain tumours in MRI images, Musa suggested a hybrid deep learning method that combines optimised Softmax Regression with ResNet-50. With an outstanding 98.4% accuracy rate, the technology outperformed current methods for automatically detecting brain tumours. This model showed notable gains in diagnostic performance, making it a useful tool for radiologists. This contrasts with previous research, which frequently struggled with restrictions including the accuracy with poor result and high computational cost [9].

This study outperforms previous research, such as that of Damodharan et al., who used a neural network that included KNN and Bayesian classifiers. Their model had issues because of the tiny dataset, which limited its generalisability even if it achieved 83% accuracy. Like this, Abiwinanda et al. used a CNN-based feature extraction method, however because preprocessing was not used, the softmax classifier's performance suffered and they only obtained 84.19% accuracy.

Mohanty and Sarmadi proposed a deep learning method for classifying brain tumours in MRI images that makes use of convolutional neural networks (CNNs). By achieving 97%

https://doi.org/10.31436/ijpcc.v11i1.510

accuracy in tumour identification and 98% accuracy in tumour classification, their model made significant improvements in better targeted treatment and early diagnosis. The system's usability and strong performance in clinical applications were shown by utilising optimisation approaches [10].

Aykat developed a deep learning model for brain tumour identification based on MRI images, using three pre-trained convolutional neural networks as feature extractors and attaining an astonishing 99.58% accuracy with four distinct classifiers. This method beat established approaches and prior CNN-based models, indicating the possibility of improved diagnostic accuracy and reliability in medical applications [11].

Leal et al. proposed a deep learning model for brain tumour classification using Convolutional Neural Networks (CNNs) on MRI images, with a focus on glioma, meningioma, and pituitary tumours. The VGG16 model beat ResNet50 and InceptionV3, having the accuracy of 98.36% and precision of 98.12%, with high recall rates and F1-scores for all tumour types, especially pituitary tumours (100% recall). ResNet50 produced comparable findings, but with lower accuracy (98.28%) and precision (97.56%), whilst InceptionV3 trailed with 93.68% accuracy and 88.56% precision. This work demonstrates VGG16's usefulness for automated brain tumour classification, proving its superiority over other models and emphasising its potential for aiding with early diagnosis and treatment planning in clinical settings.[13]

The literature review offers a thorough summary of developments in the classification of brain tumours using deep learning methods and MRI images. It successfully charts the development from older techniques that suffered from constraints like short datasets, inadequate preprocessing, and mediocre accuracy to more contemporary strategies that make use of innovative CNN architectures and hybrid models. Iterative increases in accuracy, precision, recall, and F1-scores are highlighted by the inclusion of several comparison studies, highlighting the importance of model selection and optimisation in attaining better results.

The review's critical evaluation of earlier research, highlighting both its advantages and disadvantages, is one of its main strengths. As an example, it recognises the work of scholars such as Damodharan et al. and Abiwinanda et al. but also highlights their limited generalisability and absence of preprocessing. In the same way, the review demonstrates the effectiveness of sophisticated CNNs and hybrid approaches by highlighting the notable improvements made by models such those put out by Mahesh and Yogesh, Musa, Aykat, and Leal et al.

The literature review concludes by highlighting the quick progress in classifying brain tumours and showing how each study builds on the one before it to get beyond prior challenges. The rise of highly reliable models, such as those developed by Aykat and Leal et al., suggests that deep learning methods are developing into credible tools for medical diagnosis. However, to guarantee broad application in real-world situations, further effort is required to solve issues including dataset variety, computational efficiency, and clinical validation.

III. METHODOLOGY

MRI brain tumor classification and segmentation have seen significant advancements with the application of Convolutional Neural Networks (CNNs), given their remarkable ability to capture intricate features in medical imaging. In this study, we focus on developing and evaluating CNN-based models to detect brain tumors from MRI scans. By utilizing the powerful VGG16 architecture and its hybrid variants, we aim to achieve precise classification of MRI images into "YES" or "NO" categories, indicating the presence or absence of brain tumors. Our approach leverages supervised learning on a well-curated dataset, facilitating a robust model capable of aiding in critical healthcare diagnostics (see Figure 1).

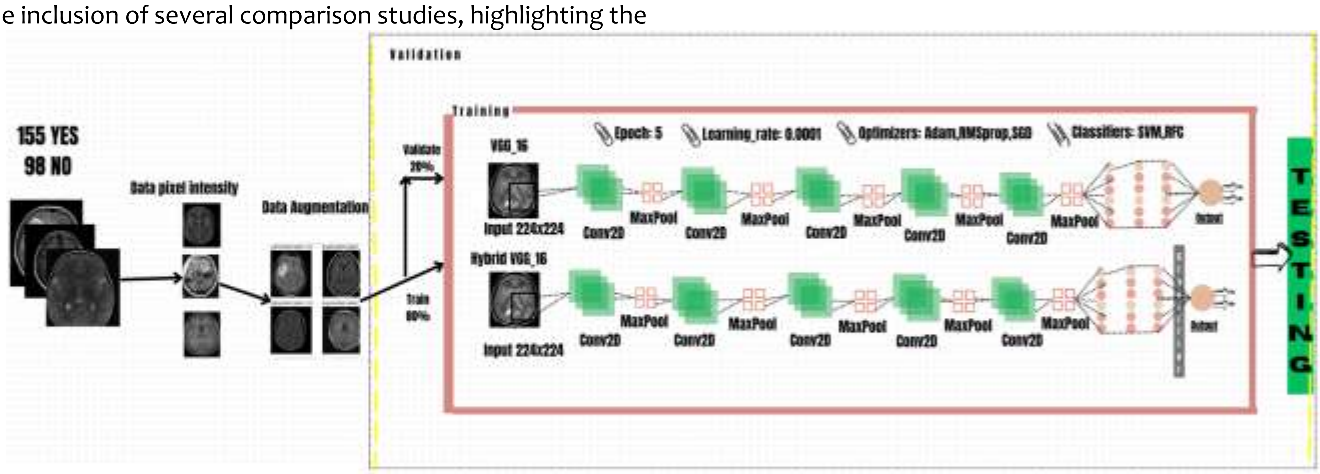


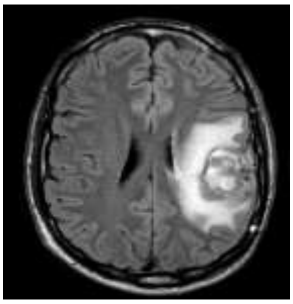
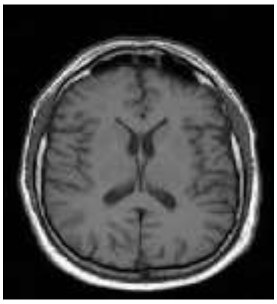
Fig 1. The Training Model

https://doi.org/10.31436/ijpcc.v11i1.510

A. Data Collection

We collected our Brain MRI image dataset from Kaggle, specifically from the "Brain MRI Images for Brain Tumor Detection" collection by Navoneel. This dataset is publicly accessible, enabling researchers to build models for brain tumor classification. Building two main models is the main goal of the project; the VGG16 design will be the focus, but there will also be other research done on hybrid VGG16 variants. Using MRI images, the models perform a binary classification task to determine if a subject has a brain tumor or not. They do this by differentiating between a "YES" class that indicates a tumor is present and a "NO" class that indicates it is not. Included in the sample are 155 occurrences labelled as "YES," indicating abnormal brain tissues with tumors, and 98 instances labelled as "NO," standing for normal brain tissues. By including both typical and unusual events, the dataset is enhanced. For supervised learning—where the models learn from labelled examples—images must be labelled as either having or not having a tumor. The hybrid version being investigated and the VGG16 architecture selected to demonstrate a purposeful approach to obtaining precise and trustworthy classification findings in this crucial healthcare (see Table 1).

TABLE I
VISUALIZATION OF SAMPLE DATASET

"YES" Labelled	"NO" Labelled
	

B. Data Preprocessing

A crucial first step in our preparation of the data for brain tumour diagnosis was finding and dropping corrupted files from the dataset. Six of the "No"-labelled files were found to be corrupted and could not be processed further. That's why, to protect the accuracy and consistency of the remaining data, these files were manually removed from the dataset. A refined dataset with 92 "No" labelled data files for the non-tumor class and 155 "Yes" labelled data files for the tumor class was obtained after this cleanup step, and the preprocessing process continued. This corruption-free selection served as the foundation for other preprocessing procedures such as pixel intensity analysis and data augmentation. Two essential steps have been combined in the data preprocessing process of our study for brain tumor detection to maximize the dataset for training machine learning models. First, a thorough examination of pixel intensities in two distinct classes "Yes" (tumor) and "No" (non-tumor) was done. Plotting pixel value histograms allowed for a thorough visualization of the distribution characteristics. This analysis made it easier to spot trends and variances in pixel brightness, which helped inform further preprocessing decisions. Based on these insights, techniques such as contrast adjustment or normalization can be customized to guarantee pixel value constancy and improve the model's ability to show features that correspond to tumors (see Figure 2 and 3).

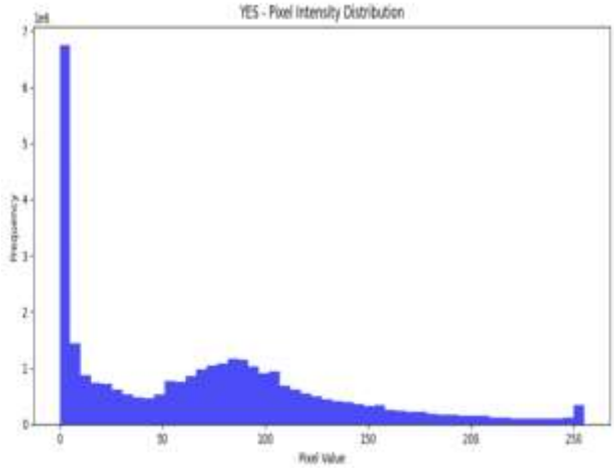


Fig 2: Distribution Characteristics of Pixel Intensity

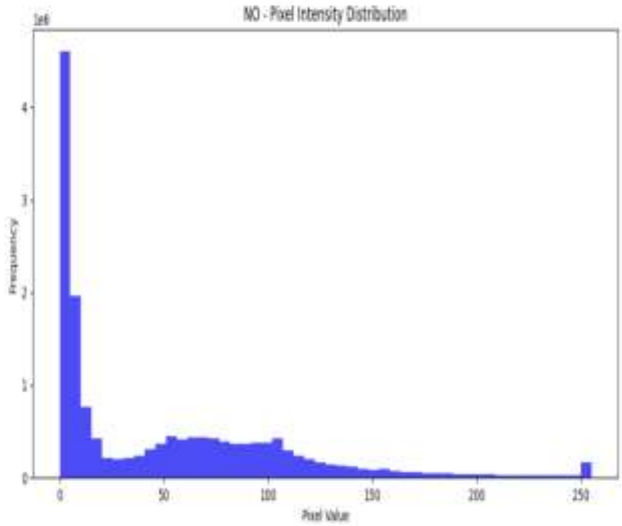


Fig 3: Distribution Characteristics of Pixel Intensity

https://doi.org/10.31436/ijpcc.v11i1.510

Additionally, picture augmentation techniques were used to enhance the dataset's diversity and enrichment even more. The training images were subjected to a variety of changes, including random height and width adjustments, horizontal flipping, and bespoke image augmentation using a custom Sequential model created with TensorFlow's "ImageDataGenerator." By adding variability to the dataset, this augmentation procedure helps the model generalize to previously unobserved data more successfully and avoids overfitting (see Figure 4 and 5).

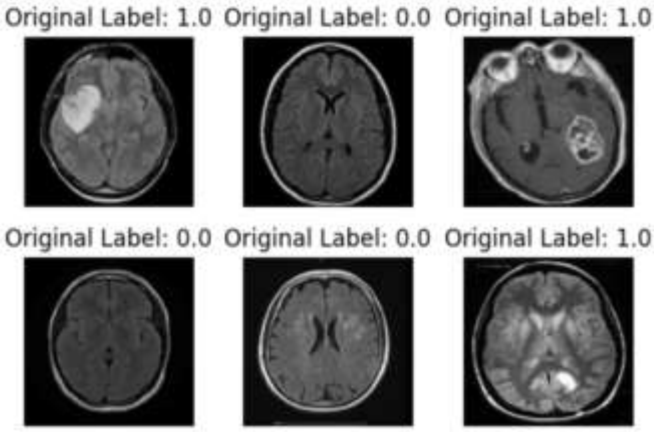


Fig 4: Original Data

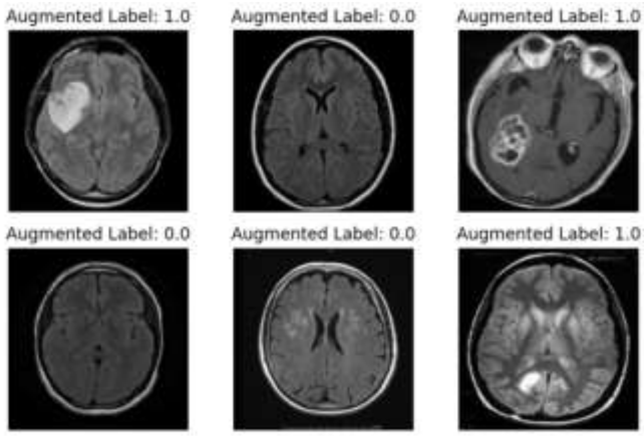


Fig 5: Augmented Data

C. *Model Architecture*

The Visual Geometry Group at the University of Oxford developed the VGG16, a deep convolutional neural network that is well-known for its ease of application and efficacy in image categorisation applications. Thirteen convolutional layers, five max-pooling layers, and three fully linked layers make up the architecture's sixteen weight layers. It is called "VGG16" because of its 16 weight layers, even though it has 21 layers overall. The convolutional layers efficiently capture local information while supporting spatial resolution by using tiny 3x3 filters with a stride of 1 and the same padding. Each block of convolutional layers is followed by max-pooling layers, which provide translation invariance and reduce computational cost by down sampling feature maps. For the ImageNet dataset, the fully connected layers are constructed with 1,000 neurones in the output layer and 4,096 neurones in the first two levels. VGG16's resilience in object identification and classification is showed by its impressive 92.7% accuracy on ImageNet. Throughout, the network uses Rectified Linear Unit (Re-LU) activation functions to introduce non-linearity. To improve generalisation, the network also periodically uses Local Response Normalisation (LRN). VGG16, a basic model in deep learning, was created for input pictures with a pixel size of 224 x 224. Its balanced design and constant use of tiny filters have sparked advances in both research and real-world applications.

D. Data Training

Using the VGG16 architecture, a binary classification model for brain tumor detection was developed during the training phase. First, extra thick layers were added to the pre-trained VGG16 base that served as the model's foundation, leaving off the top classification layer. To preserve learned features, the layers of the basic model were frozen. The model was then constructed using various optimizers, such as Adam, RMSprop, and SGD. The model was also constructed with two traditional machine learning classifiers such as SVM and RFC. After that, the model was trained through five epochs using the training dataset. The training procedure involved minimizing the divergence between the expected and actual labels by iteratively modifying the model's weights depending on the computed loss. The model's generalizability to previously unknown data was assessed by analysing its performance on a different validation dataset. Accuracy and loss were among the training parameters that were examined to evaluate the convergence and performance of the model.

E. *E. Data Testing*

During the testing phase, the validation dataset was used to assess the trained model's performance on fresh, unseen samples. In addition, the pre-trained VGG16 model was used to extract features using other classifiers like Random Forest and Support Vector Machines (SVM). The validation dataset was used to test these classifiers once they had been trained using the acquired features. To determine how well each model performed in comparison to the others, the attained accuracies were compared. Notably, the RMSprop optimizer-equipped VGG16 model showed the highest validation accuracy at 82.35%, highlighting the importance of optimization decisions for model performance. An efficient brain tumor detection system has been produced by following a methodical process from data collection, preprocessing, model architecture design, training, and testing phases. This method provides a dependable tool for precise brain tumor diagnosis, proving the potential of machine learning in medical diagnostics. Sustained efforts to improve the model will be essential to its success in practical healthcare applications.

IV. Results and Discussion

Metrics like precision and recall are often prioritized in medical diagnosis and research, and the AUC/ROC curve offers information on the efficacy of the model. In instances where datasets are imbalanced, as is prevalent in real-world medical settings, precision—which measures the accuracy of positive predictions—and recall—which measures the model's ability to detect all actual positive cases—become extremely important. As an example, we can consider COVID-19 detection, where it is crucial to avoid false negative results because of the virus's infectious nature. The most important thing is to make sure the right steps are taken to stop the spread and not mistakenly categorize a patient who tests positive for COVID-19 as negative. When diagnosing high-risk diseases like cancer or brain tumors, recall becomes a more important evaluation criterion than precision. Since false positives typically have less of an impact, it is undesirable to miss actual positives. A false negative in these circumstances could have serious repercussions and put the patient's life in danger.

When it comes to brain tumor identification, it is crucial to avoid false negative results because of the condition's possible severity. Ensuring prompt medical interventions and therapies for patients with brain tumors depends on the precise identification of those affected. In this situation, false negative results could cause a delay in diagnosis and treatment, which could have an impact on patient outcomes. Reducing false negatives is crucial when dealing with high-risk conditions like brain tumors to prevent situations that need immediate medical treatment from going unnoticed. We have calculated validation accuracy for all our models. The percentage of right predictions a machine learning model makes on a different dataset that was not used for training is known as validation accuracy. It aids in evaluating the model's ability to generalize to fresh, untested data. Precision and recall metrics are typically more important than accuracy in medical cases and diagnosis. Achieving a balance between false positives and false negatives is crucial in medical circumstances. aiming for high recall is often more crucial in situations where false negatives—missing a positive case—can have serious repercussions for the patient than aiming for overall accuracy. For patient outcomes and public health, precision and recall offer more detailed insights into a model's performance in recognizing positive cases and preventing false negatives.

The discrimination ability of a model is evaluated by the AUC/ROC curve, which shows the trade-off between recall and precision. More recall is indicated by a steeper ROC curve, even though it does not directly show precision and recall. The AUC/ROC curve supports precision-recall calculations in medical instances, particularly when there is imbalanced data. It offers information on how effectively a model strikes a balance between recall and precision for efficient disease identification. The F1 score is a metric that combines both precision and recall into a single value. While analyzing the result, a huge focus has been placed on the results of the Yes subset as well as on Recall and Precision.

In our analysis, both VGG16 + Adam Optimizer and VGG16 + RMSprop Optimizer achieved good overall accuracy (80.39% and 82.35%, respectively). However, when considering the AUC curve, VGG16 + Adam performed better with a score of 54.04%. Upon closer examination of recall results for the "Yes" subfolder, VGG16 + Adam showed superior performance, capturing more actual positive cases. Meanwhile, for precision in the "Yes" subfolder, VGG16 + RMSprop outperformed.In the "No" subfolder, VGG16 + RMSprop demonstrated better results across precision, recall, and F1 Score.To summarize, while VGG16 + Adam excelled in overall AUC, VGG16 + RMSprop showed strengths in precision, recall, and F1 Score, particularly for the "No" subfolder. The VGG16 + SGD Optimizer attained ROC/AUC 45.29% which is considered poor, and performed well for the 'Yes' subfolder, giving a perfect score of 1.00 for recall, 0.65 for Precision, hence having a higher F1 Score of 0.79.But the precision, recall and F1 Score for the 'No' subfolder is 0.A recall of 0 for the "No" class suggests that the model is missing all instances of the positive class within the "No" category. Based on performance coming in next is the VGG16 + RFC hybrid algorithm, having 0.61 Precision and 0.70 recall for the 'Yes' subfolder and 0.23 precision, and 0.17 recall for No subfolder.The last algorithm explained is the VGG16 + SVM hybrid algorithm, it has maintained the same score of Precision, recall, and F1 score, 0.61 for 'Yes' as well as the same score of Precision, recall, and F1 score, 0.28 for 'No' subfolder (see Table 2).

TABLE II
PERFORMANCE EVALUATION OF THE MODELS

MODEL	VALIDATION ACCURACY	ROC-AUC	PRECISION	RECALL	F1-SCORE
VGG16 +ADAM OPTIMIZER	80.39%	54.04%	YES:0.67	0.79	0.72
			NO:0.42	0.28	0.33
VGG16 + RMSPROP OPTIMIZER	82.35%	46.805%	YES: 0.69	0.76	0.72
			NO: 0.47	0.39	0.42
VGG16 + SGD OPTIMIZER	64.71%	45.29%	YES:0.65	1.00	0.79
			NO:0.0	0.0	0.0
VGG16 + RFC	64.71%	42.85%	YES:0.61	0.70	0.65
			NO:0.23	0.17	0.19
VGG16 + SVM	47.06%	39.06%	YES:0.61	0.61	0.61
			NO: 0.28	0.28	0.28

V. CONCLUSION

By advancing better healthcare results, our research on developing a trustworthy hybrid model for brain tumor classification is in line with medical and sustainable development objectives. One of the main goals of sustainable development is to promote health and well-being. We address the crucial need for precise medical diagnoses, guaranteeing prompt interventions and therapies for patients with brain tumors, by giving precision and recall top priority in our models. The incorporation of advanced approaches such as the DCNN VGG16, RFC, and SVM highlights the dedication to using technology to improve medical decision-making, which is in line with guaranteeing healthy lives and fostering well-being for everybody.

In addition, our focus on customized metrics and hybrid techniques shows our dedication to the advancement of medical technology and research, which is a crucial part of sustainable development. We work to improve the effectiveness and dependability of brain tumor identification by combining machine learning models with conventional classifiers, supporting the overall goal of reaching universal health care and minimizing health disparities. The AUC/ROC curve's complex interpretation shows our commitment to fine-tuning models for practical medical applications, which will lead to more patient outcomes and sustainable healthcare practices.

Future research should focus on fine-tuning model parameters, optimizing learning rates for optimizers, and adjusting parameters related to Random Forest Classifier (RFC) to enhance overall model performance. Implementing advanced data augmentation techniques customized for medical imaging can contribute to better generalization. Exploring ensemble approaches that combine deep learning, and traditional classifiers may lead to potential performance improvements. Ensuring model interpretability through techniques like SHAP or LIME is crucial for showing trust in clinical settings. Addressing class imbalance, obtaining validation from clinical experts using diverse datasets, and conducting robustness testing across varying imaging conditions are essential for practical applicability. In summary, refining parameters, improving interpretability, and addressing practical challenges are critical areas for future research to confirm the model's effectiveness in clinical practice.

ACKNOWLEDGMENT

The authors hereby acknowledge the review support offered by the IJPCC reviewers who took their time to study the manuscript and find it acceptable for publishing.

CONFLICT OF INTEREST

The authors declare that there is no conflict of interest

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