Integrative Approaches for Accurate Brain Tumor Classification: A Comparative Study of Deep Learning and Traditional Machine Learning Models

Md. Hasibul Islam
Department of Computer Science & Engineering
Ahsanullah University of Science and Technology
Dhaka, Bangladesh
md.hasib.02020@gmail.com

Farhan Abid Ahmed
Department of Computer Science & Engineering
Ahsanullah University of Science and Technology
Dhaka, Bangladesh
f.dipto5@gmail.com

Aurprita Mahmood
Department of Computer Science & Engineering
Ahsanullah University of Science and Technology
Dhaka, Bangladesh
aurprita1234@gmail.com

Meherin Sultana
Department of Computer Science & Engineering
Ahsanullah University of Science and Technology
Dhaka, Bangladesh
sultanameh01@gmail.com

***Abstract*—This paper addresses the critical issue of brain tumor detection and classification using advanced machine learning and deep learning techniques. Brain tumors, comprising benign and malignant types, necessitate early identification for successful treatment. The study explores the application of Convolutional Neural Networks (CNNs) such as VGG16, Support Vector Machines (SVM), K-Nearest Neighbors (KNN), and Random Forest for accurate and automated brain tumor classification. Leveraging a comprehensive dataset encompassing glioma, meningioma, pituitary, and no tumor classes, the models are rigorously evaluated, with the CNN model demonstrating superior accuracy. The results provide valuable insights for researchers and practitioners in the field of medical image classification.**

***Index Terms*—Tumor, Brain Tumor, MRI, Transfer Learning, CNN, VGG-16, SVM, KNN**

I. Introduction

Brain tumors pose a significant challenge in the field of medical diagnostics, demanding precise and efficient classification for effective treatment planning. As medical imaging technologies advance, machine learning models emerge as powerful tools for automating the intricate task of brain tumor classification in magnetic resonance imaging (MRI) scans. This paper explores an integrative approach, combining state-of-the-art deep learning techniques with traditional machine learning models, to achieve accurate and comprehensive brain tumor classification.

The study focuses on leveraging diverse machine learning models, including Convolutional Neural Networks (CNN) with a VGG16 base, Support Vector Machines (SVM), K-Nearest Neighbors (KNN), and Random Forest, for the classification of brain tumors. Each model brings a unique set of strengths, allowing for a holistic examination of their performance across distinct types of brain tumors, such as glioma, meningioma, and pituitary tumors.

Accurate brain tumor classification is paramount for timely and targeted medical interventions. Misclassifications or delays in diagnosis can have profound consequences on patient outcomes. By employing both deep learning and traditional machine learning models, this research aims to address the nuances associated with different tumor types, offering insights into the strengths and limitations of each model in varying clinical scenarios.

The methodology involves preprocessing a comprehensive dataset comprising MRI images of diverse brain tumors. The CNN model with a VGG16 base undergoes fine-tuning, while traditional machine learning models utilize features such as Histogram of Oriented Gradients (HOG). The study rigorously evaluates each model's performance using key metrics, including accuracy, precision, recall, and F1-score. A comparative analysis sheds light on the suitability of models for specific tumor types, contributing to a nuanced understanding of their applications in clinical practice.

II. Literature Review

Brain tumors present a significant challenge in the medical field due to their complexity and potential life-threatening consequences. The emergence of advanced imaging techniques, particularly Magnetic Resonance Imaging (MRI), has played a pivotal role in diagnosing and understanding brain tumors. Over time, researchers and medical professionals have sought to improve the accuracy and efficiency of brain tumor detection (Hammad et al., 2023) [5] and classification through various computational methods, particularly leveraging Machine Learning (ML) and Deep Learning (DL) approaches.

The application of ML and DL techniques in brain tumor detection has shown promise, surpassing the accuracy levels achievable through manual diagnosis. Convolutional Neural Networks (CNNs), Artificial Neural Networks (ANNs), and Transfer Learning (TL) stand out as prominent methodologies used in the classification and segmentation of brain tumor images obtained from MRI scans.

Previous research has demonstrated the effectiveness of CNNs in automatically detecting and categorizing brain tumors from MRI images, achieving high accuracy rates and outperforming traditional diagnostic methods. Furthermore, Transfer Learning has shown potential in utilizing pre-trained models to classify brain tumor images, exhibiting robustness and scalability across diverse datasets.

Despite advancements, challenges persist, particularly in handling diverse abnormalities in tumor sizes, locations, and complexities observed in real-world MRI images. Datasets used in these studies, such as collaborative datasets curated by researchers, play a crucial role in advancing brain tumor research. However, issues related to class imbalance, dataset consistency, and standardization across varying MRI image sizes are areas warranting further exploration.

Moreover, the preprocessing steps applied to these datasets, including resizing images, eliminating extraneous margins, and refining image quality, have been emphasized to enhance model performance and accuracy.

The proposed dataset and its constituent datasets, encompassing glioma, meningioma, pituitary, and no tumor classes, hold promise in addressing existing challenges. Further exploration and enhancement of this dataset, coupled with rigorous algorithm development, have the potential to revolutionize brain tumor diagnostics. This advancement could significantly improve patient outcomes and advance medical practices in the field of neuroimaging.

The paper (Amin et al., 2022) [1] emphasizes a classification scheme for brain tumor MRI images, compatible with CNN and utilizing datasets for computerized CNN manipulation. Additionally, it leverages Deep Learning based approaches for automatic feature extraction, enhancing effectiveness and robustness in classification and detection tasks.

To categorize brain tumors based on MRI results (Hossain et al., 2019) [2], the photographs are split up into three groups by the application. Pre-processing has to be done on the photos first. Following scaling, a Gaussian filter is used to smooth and equalize the histogram of each image. After preprocessing, the pictures are put into a CNN architecture with five layers. The final data shows that the recommended technique achieves an average precision of 93.33% and an accuracy of 94.39 percent. When the authors' training accuracy and loss graphs were compared to other cutting-edge models, the findings were positive.

An advanced Deep Learning technique (Siar et al., 2019) [3] created specifically for brain tumors. Their recommended approach begins with a thorough analysis of (CNNs) using three different classifiers: the Radial Basis Function, the SoftMax layer, and Decision Trees. Unexpectedly, the SoftMax layer turned out to be the most successful in helping the classifier achieve the highest accuracy. To obtain important data, the model conveniently integrates with the primary clustering procedure. Following the collection of these features, the CNN method is suggested. To help with classification, a fully linked SoftMax layer is added. The proposed methodology has demonstrated remarkable accuracy, with a 96% accuracy rate, through thorough experimentation. Deep Learning has become an amazing technology that can process large amounts of substantial data, outperforming many traditional methods.

Using an iterative process (Abdusalomov et al., 2023) [4], the central clustering method finds the mean points that belong to each cluster, or cluster centers. The algorithm assigns a cluster center that is closest to each data sample. In the simplest implementation of this method, the first cluster centers are selected at random.

Five models (Shawon et al., 2023) [6] Convolutional Neural Network (CNN), ResNet50, InceptionV3, EfficientNetB0, and NASNetMobile were used for brain tumor detection, achieving a remarkable accuracy of 99.33% with ResNet50 and InceptionV3 with an incredible recall value of 0.9867. Also, Explainable AI and a cost-sensitive neural network approach were used for imbalanced dataset.

III. Background Study

Brain tumors present a significant health challenge, impacting patient prognosis and treatment strategies. Accurate and timely detection is crucial for effective interventions. Manual diagnostic methods are error-prone, necessitating precise and automated detection techniques. In medical imaging, Deep Learning, especially Convolutional Neural Networks (CNNs), has emerged as a powerful tool. CNNs, trained on labeled brain image datasets and empowered by preprocessing steps like resizing and augmentation, exhibit remarkable capabilities in accurately discerning tumor presence, enhancing the potential for precise classification.

Three prominent deep learning architectures are extensively employed for brain tumor detection:

A. Convolutional Neural Network (CNN)

Convolutional Neural Networks (CNNs) are a type of deep learning model that has proven to be effective in various computer vision tasks, including medical image analysis. Detecting brain tumors using CNNs involves training the model on a dataset of brain images and then using it to classify new images as either containing a tumor or not. CNN works with a labeled dataset of brain images, where each image is annotated with information about the presence or absence of a tumor. Preprocess the images to ensure consistency and improve the model's ability to learn relevant features. This may involve resizing, normalization, and augmentation to increase the size and diversity of the dataset.

B. VGG (Visual Geometry Group) Networks

The VGG-16 (Visual Geometry Group - 16 layers) is a convolutional neural network (CNN) architecture that has been widely used for image classification tasks, and it can be applied to the detection of brain tumors as well. VGG-16 is characterized by its simplicity and uniformity in architecture. It consists of 16 layers, including 13 convolutional layers and 3 fully connected layers. The convolutional layers use small 3x3 filters with a stride of 1 and max-pooling layers with 2x2 filters. Initialize the VGG-16 model with pre-trained weights on a large dataset (e.g., ImageNet). This is a form of transfer learning, where the model has already learned generic features from a diverse set of images. Fine-tune the model on the brain tumor dataset by replacing the last few layers and training the model specifically for tumor detection. Adjust the weights using backpropagation and gradient descent.

C. Residual Networks (ResNets)

ResNet50 consists of 50 layers, including residual blocks. The key innovation in ResNet is the use of skip connections (or shortcut connections) that allow the gradient to flow directly through the network. This helps in training very deep networks without suffering from the vanishing gradient problem. Initialize the ResNet50 model with pre-trained weights on a large dataset (e.g., ImageNet). Transfer learning leverages the features learned by the model on a diverse set of images to boost performance on the brain tumor dataset. Modify the last few layers of the ResNet50 model to match the number of classes in your brain tumor dataset. This involves replacing the final fully connected layer with a new layer that has the appropriate number of output nodes for tumor detection.

Moreover, machine learning models like SVM, KNN, and RF can be used besides the above-mentioned deep learning models. These models - SVM, KNN, and Random Forest - offer distinct approaches to brain tumor prediction, and their application depends on factors like dataset characteristics and the specific requirements of the task at hand. Hyperparameter tuning and careful consideration of dataset nuances are crucial for optimizing their performance.

D. Support Vector Machines (SVM)

Support Vector Machines (SVM) is a powerful supervised learning algorithm utilized in brain tumor prediction. In this application, SVM excels at classifying images based on features extracted from the tumors. By finding an optimal hyperplane in a high-dimensional feature space, SVM effectively separates tumor and non-tumor classes, contributing to accurate predictions.

E. K-Nearest Neighbors (KNN)

K-Nearest Neighbors (KNN) is an intuitive classification algorithm widely employed in brain tumor image analysis. Operating on the principle of similarity, KNN classifies brain tumor images by comparing their feature vectors with those of neighboring images. The algorithm's simplicity and effectiveness make it suitable for cases where the relationship between features and classes is locally consistent.

F. Random Forest (RF)

In the realm of brain tumor prediction, Random Forest emerges as a robust ensemble learning method. By constructing multiple decision trees during training, Random Forest leverages the strength of each tree's individual predictions. Applied to brain tumor images, this model combines the outputs of numerous decision trees, providing a reliable classification mechanism. The ensemble approach enhances predictive accuracy and handles diverse patterns in brain tumor data effectively.

IV. Dataset Description

The Brain Tumor MRI dataset is a comprehensive collection sourced from multiple datasets, primarily comprising a total of 10307 MRI images of human brains, meticulously categorized into four distinct classes—glioma, meningioma, pituitary, and no tumor. These images are pivotal in the domain of brain tumor classification and detection.

The dataset amalgamates contributions from various sources, notably including the figshare repository, SARTAJ dataset, and Br35H. However, due to inconsistencies within the SARTAJ dataset's glioma class categorization, a careful refinement process was undertaken. In response to observed discrepancies evident in both personal experimentation and third-party analysis, the glioma class images from the SARTAJ dataset were omitted, and instead, the figshare repository's images were integrated for improved dataset integrity.

Each MRI image encapsulates the complexity of brain tumors, portraying a diverse range of abnormalities in size and location within the brain. Notably, these images vary in sizes, mandating a preprocessing step to standardize dimensions for improved model accuracy and efficiency. The dataset, primarily composed of Magnetic Resonance Imaging (MRI) scans, offers a diverse and rich set of images that emulate real-world scenarios encountered in clinical settings.

This dataset serves as an invaluable asset for the development and evaluation of automated classification techniques. Leveraging state-of-the-art Deep Learning Algorithms encompassing Convolutional Neural Networks (CNNs), Artificial Neural Networks (ANNs), and Transfer Learning (TL), it enables the construction of models exhibiting enhanced accuracy and efficacy in brain tumor classification and detection tasks.

The dataset was compiled and made available for research purposes through the collaborative efforts of Navoneel Chakrabarty, Swati Kanchan, Sartaj Bhuvaji, Ankita Kadam, Prajakta Bhumkar, and Sameer Dedge. The dataset amalgamated information from multiple sources, including figshare, SARTAJ dataset, and Br35H, to curate a comprehensive collection of brain MRI images for the purpose of brain tumor classification and detection research.

V. Methodology

Our paper proposes and evaluates various machine learning models for brain tumor classification using MRI images. The methodology consists of the following steps:

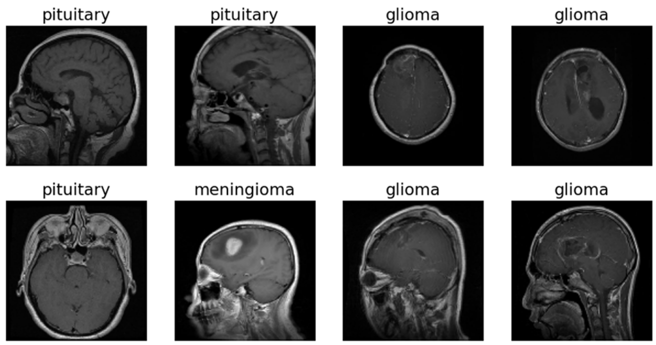

Fig. 1. Few sample instances of different types of tumor.

A. Dataset Preprocessing

The dataset consists of MRI images of different types of brain tumors, such as glioma, meningioma, and pituitary. The images have varying dimensions, which need to be standardized for efficient and accurate model training and testing. Therefore, a preprocessing step is applied to resize all the images to 224x224 pixels, which is the input size for the VGG16 model. The resized images are then saved as numpy arrays for further processing.

B. Model Selection and Implementation

The paper utilizes four different models for brain tumor classification: a CNN model with VGG16 base, an SVM model with HOG features, a KNN model, and a Random Forest model. Each model is implemented and evaluated using the following steps:

- **CNN Model with VGG16 Base:** A CNN model is a type of deep learning model that can learn features from images using convolutional layers. The VGG16 model is a pretrained CNN model that has been trained on a large dataset of images called ImageNet. The paper uses the VGG16 model as the base architecture for the CNN model and fine-tunes it for the brain tumor classification task. The fine-tuning process involves setting most of the VGG16 layers to non-trainable, except for the last convolutional block, which is made trainable to adapt to the new task. Additional layers, such as Flatten, Dropout, and Dense layers, are added on top of the VGG16 model to perform feature extraction and classification. The model is compiled using the Adam optimizer with a learning rate of 0.0001 and sparse categorical crossentropy as the loss function. The model is trained for 10 epochs with a batch size of 25 using the resized MRI images as input and the tumor labels as output.
- **SVM Model with HOG Features:** An SVM model is a type of machine learning model that can perform classification by finding the optimal hyperplane that separates the data points of different classes. HOG features are a type of image features that capture the distribution of gradient orientations in an image. The paper uses HOG features as the input for the SVM model, as they can capture the shape and texture of the tumors. The HOG features are extracted from the resized MRI images using the skimage library. A linear SVM model is trained using the HOG features and the tumor labels. The dataset is split into training and testing sets, and the HOG features are converted to PyTorch tensors for compatibility with the SVM model. The training time and the predictions of the SVM model are recorded and evaluated.

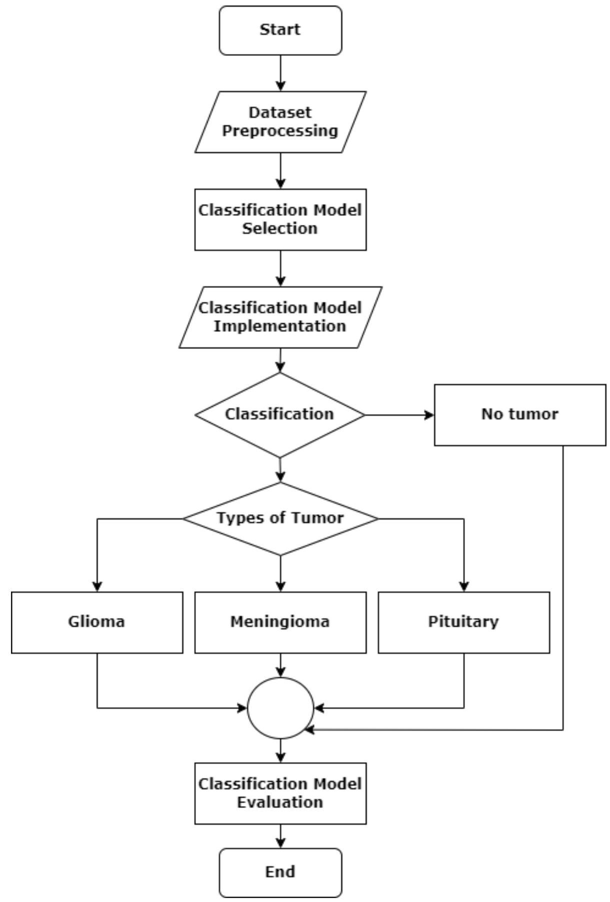

Fig. 2. Steps involved in identification of the different types of tumor.

- **K-Nearest Neighbors (KNN) Model:** A KNN model is a type of machine learning model that can perform classification by finding the k-nearest neighbors of a data point and assigning it the majority class label among them. The paper uses the same HOG features as the input for the KNN model, as they can represent the similarity between the images. The paper chooses 15 as the number of neighbors for the KNN model, based on empirical testing. The KNN model is trained and tested using the HOG features and the tumor labels. The training time and the predictions of the KNN model are recorded and evaluated.
- **Random Forest Model:** A Random Forest model is a type of ensemble learning model that can perform classification by combining the predictions of multiple decision

trees. A decision tree is a type of machine learning model that can perform classification by splitting the data points based on certain criteria. The paper uses the same HOG features as the input for the Random Forest model, as they can capture the diversity and complexity of the images. The paper chooses 100 as the number of estimators for the Random Forest model, based on empirical testing. The Random Forest model is trained and tested using the HOG features and the tumor labels. The training time and the predictions of the Random Forest model are recorded and evaluated.

C. Model Evaluation

The paper evaluates the performance of each model using various metrics, such as accuracy, precision, recall, and F1-score. These metrics measure the ability of the models to correctly classify the different types of brain tumors and avoid misclassification errors. The paper also compares the performance of the SVM, KNN, and Random Forest models with the CNN model, which serves as the baseline. The paper analyzes the strengths and weaknesses of each model and discusses the implications for the brain tumor classification task.

VI. Result Analysis

This section presents a comprehensive analysis of the results obtained from the experimentation with both deep learning and traditional machine learning models for brain tumor classification using MRI images. The models under consideration are a Convolutional Neural Network (CNN) with a VGG16 base and three machine learning models - Support Vector Machine (SVM) with Histogram of Oriented Gradients (HOG) features, K-Nearest Neighbors (KNN), and Random Forest.

A. CNN with VGG16 Base:

- The CNN model with a VGG16 base achieved an overall accuracy of 93%, demonstrating robust performance across multiple tumor classes.
- Noteworthy precision, recall, and F1-score metrics were observed for all classes, indicating a balanced classification capability.
- Training and classification time was approximately 39 minutes and 50 seconds, reflecting the computational intensity of deep learning models.

TABLE I
Performance of CNN on the dataset

Class	Precision	Recall	F1 Score	Accuracy
Glioma	92.00	81.00	86.00	93.00
Meningioma	91.00	92.00	92.00	
No tumor	94.00	100.00	97.00	
Pituitary	94.00	98.00	96.00	

B. SVM with HOG Features:

- The SVM model with HOG features demonstrated an accuracy of 91.38%, performing competitively with the CNN model.
- Precision, recall, and F1-score metrics exhibited consistency, suggesting a reliable classification across different tumor types.
- Despite a longer training and classification time (362.69 seconds), the SVM model showcased the efficacy of traditional machine learning in the context of feature-based image classification.

TABLE II
Performance of SVM on the dataset

Class	Precision	Recall	F1 Score	Accuracy
Glioma	94.00	73.00	83.00	91.00
Meningioma	87.00	92.00	90.00	
No tumor	91.00	100.00	95.00	
Pituitary	95.00	98.00	96.00	

C. K-Nearest Neighbors (KNN):

- The KNN model achieved an accuracy of 85.40%, demonstrating its competence in the classification task.
- Balanced precision, recall, and F1-score metrics indicated a stable performance across the tumor classes.
- The KNN model showcased swift training and classification times (3.84 seconds), emphasizing its simplicity and efficiency for certain scenarios.

TABLE III
Performance of KNN on the dataset

Class	Precision	Recall	F1 Score	Accuracy
Glioma	92.00	75.00	82.00	85.00
Meningioma	88.00	73.00	80.00	
No tumor	82.00	96.00	89.00	
Pituitary	82.00	96.00	89.00	

D. Random Forest:

- The Random Forest model achieved an accuracy of 86.86%, presenting competitive results in comparison to both CNN and SVM models.
- Precision, recall, and F1-score metrics showcased stability in classification across different tumor classes.
- The Random Forest model's training and classification time (227.60 seconds) positioned it as a viable alternative to more complex deep learning models.

Comparative Analysis:

- The CNN model demonstrated superior accuracy, precision, recall, and F1-score metrics compared to traditional machine learning models, highlighting its proficiency in extracting hierarchical features from complex image data.

TABLE IV
PERFORMANCE OF RANDOM FOREST ON THE DATASET

Class	Precision	Recall	F1 Score	Accuracy
Glioma	91.00	64.00	75.00	87.00
Meningioma	84.00	87.00	85.00	
No tumor	88.00	99.00	93.00	
Pituitary	86.00	95.00	90.00	

- Traditional machine learning models, particularly SVM and Random Forest, showcased competitive results, proving their effectiveness in scenarios where computational resources are constrained or interpretability is crucial.
- The simplicity and efficiency of KNN, as evidenced by its quick training and classification times, make it a viable choice for certain real-time applications, despite a slightly lower accuracy compared to more complex models.

TABLE V
PERFORMANCE COMPARISON OF DIFFERENT MODELS

Model	Accuracy	Precision	Recall	F1 Score
SVM	91.37	91.58	91.37	91.09
KNN	85.39	86.04	85.39	85.07
Random Forest	86.86	87.16	86.86	86.27

The choice between deep learning and traditional machine learning models depends on the specific requirements of the task at hand. Deep learning models, such as CNNs, excel in scenarios where complex hierarchical features are crucial, while traditional machine learning models offer competitive performance with computational efficiency and interpretability advantages. The results emphasize the significance of a nuanced approach, selecting models based on the intricacies of the classification task and available computational resources. The findings provide valuable insights for researchers and practitioners working in the domain of medical image classification, paving the way for informed model selection based on specific use cases.

VII. LIMITATIONS AND FUTURE WORK

While the current research has provided valuable insights into the efficacy of Convolutional Neural Networks (CNNs) and traditional machine learning models for brain tumor classification, there are several avenues for future exploration and improvement.

Future research can explore the integration of advanced deep learning architectures such as ResNet, MobileNet, InceptionV3, and others. These architectures may capture more intricate features and patterns in the MRI images, potentially leading to improved classification performance. Comparative studies between various architectures would provide a deeper understanding of their effectiveness in the context of brain tumor classification.

A comprehensive exploration of hyperparameter tuning could significantly impact model performance. Fine-tuning parameters such as learning rates, dropout rates, and batch sizes for both deep learning and traditional machine learning models may lead to optimized configurations, potentially improving accuracy and reducing training times. Automated hyperparameter optimization techniques, including grid search and random search, could be employed to efficiently navigate the hyperparameter space.

Building upon the success of transfer learning with VGG16, future work can incorporate other pre-trained models and explore various transfer learning variants. Leveraging pre-trained models on larger datasets may enhance the generalization ability of the models. Additionally, investigating domain adaptation techniques could prove beneficial in scenarios where the source and target domains exhibit variations.

VIII. CONCLUSION

In conclusion, this paper tackles brain tumor classification using a holistic approach combining deep learning and traditional machine learning models. The CNN with VGG16 achieves a remarkable 93% accuracy, demonstrating robust performance across tumor classes. Traditional models like SVM, KNN, and Random Forest also perform competitively, highlighting their effectiveness in specific scenarios.

The choice between deep learning and traditional models hinges on task-specific needs like computational resources and interpretability. This paper provides nuanced insights for researchers, aiding informed model selection based on task intricacies.

Future research directions include exploring advanced deep learning architectures, thorough hyperparameter tuning, and refining transfer learning techniques. These avenues have the potential to enhance brain tumor classification models, advancing neuroimaging and patient outcomes. The proposed diverse tumor dataset is a valuable resource for future research in brain tumor diagnostics. Overall, this work sets the stage for ongoing exploration and improvement in automated brain tumor classification.

REFERENCES

[1] Amin, J., Sharif, M., Haldorai, A., Yasmin, M., & Nayak, R. S. (2022). Brain tumor detection and classification using machine learning: a comprehensive survey. Complex & intelligent systems, 8(4), 3161-3183.

[2] Hossain, T., Shishir, F. S., Ashraf, M., Al Nasim, M. A., & Shah, F. M. (2019, May). Brain tumor detection using convolutional neural network. In 2019 1st international conference on advances in science, engineering and robotics technology (ICASERT) (pp. 1-6). IEEE.

[3] Siar, M., & Teshnehlab, M. (2019, October). Brain tumor detection using deep neural network and machine learning algorithm. In 2019 9th international conference on computer and knowledge engineering (ICCKE) (pp. 363-368). IEEE.

[4] Abdusalomov, A. B., Mukhiddinov, M., & Whangbo, T. K. (2023). Brain tumor detection based on deep learning approaches and magnetic resonance imaging. Cancers, 15(16), 4172.

[5] Hammad, Mohamed, Mohammed ElAffendi, Abdelhamied A. Ateya, and Ahmed A. Abd El-Latif (2023, May). Efficient Brain Tumor Detection with Lightweight End-to-End Deep Learning Model. Cancers 15, no. 10: 2837.

[6] Shawon, Md Tanvir R., Shibli, G. M. Shahariar, Farzad A., & Joy, Sajib K. S. (2023, August). Explainable Cost-Sensitive Deep Neural Networks for Brain Tumor Detection from Brain MRI Images considering Data Imbalance.