Hybrid Feature-based Machine Learning Framework for Automated Brain Tumor Classification

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ABSTRACT The classification of brain tumors using Magnetic Resonance Imaging (MRI) is crucial for early diagnosis and efficient decision-making in clinical practice. However, manual analysis is a time-consuming process that may introduce observer bias. To address these issues, the current study presented a hybrid feature-based Machine Learning (ML) model for automated brain tumor classification, integrating both handcrafted and Deep Learning (DL) features to enhance robustness and accuracy. The suggested method combines Histogram of Oriented Gradients (HOG) to retrieve local texture data and high-level semantic details obtained with the help of the ResNet-50 deep convolutional neural network (CNN). The hybrid feature vectors are then classified with various ML classifiers, such as Linear, Gaussian, and Quadratic Support Vector Machines (SVMs), Logistic Regression (LR), Random Forest (RF), and XGBoost. The model was tested using two publicly-available benchmark datasets, viz., the Figshare Brain Tumor MRI dataset and Harvard Brain Tumor MRI dataset of a total of 10,286 MRI images. The experimental findings showed that the hybrid framework is best in the Figshare dataset, where Quadratic SVM has the best classification accuracy of 97%, and the other models are 96% and 95% with Gaussian SVM and LR, respectively. RF yields optimal accuracy on the more difficult Harvard dataset at 76%, which means that the proposed approach can be generalized to diverse data distributions. A further study is an ablation study, which supports the claim that the combination of handcrafted and deep features is a significant performance metric on classification when compared to the features separately. The findings confirmed that the hybrid framework has been developed as a suitable, robust, and universalized framework to classify automated multi-class brain tumors with the help of MRI images.

INDEX TERMS Brain tumor classification, deep learning, MRI, hybrid feature model, ResNet-50, Support Vector Machine, Random Forest.

I. INTRODUCTION

Brain tumors represent one of the most dangerous neurologic disorders with a high mortality rate in case of late diagnosis. Thus, there is a need for the proper diagnosis of these tumors for an effective and timely treatment. In clinics, Magnetic Resonance Imaging (MRI) offers a high level of soft tissue contrast and allows seeing the morphology of a tumor in detail [1]. Nevertheless, manual analysis of MRI images is time-consuming and may be subject to inter-observer error, which constrains diagnostic process in a clinical setting. Machine Learning (ML) and Artificial Intelligence (AI) algorithms have demonstrated high potential in the detection and classification of brain tumors. These algorithms have led to a higher level of accuracy, less time to diagnose a patient, and even aided them in making clinical decisions [2].

The most recent developments in ML and hybrid modeling methods have improved MRI-based brain tumor classification systems considerably. The classic ML algorithms, Support Vector Machines (SVM), Random Forest (RF), and K-

Nearest Neighbors (KNN) are still among the most commonly used algorithms. These are widely recognized due to their strength and interpretability when used with handcrafted or engineered features of imaging data. As an example, as it has been shown, combinations of texture, histogram, and shape-based features with classifiers, such as SVM and RF result in high-level performance of classification, which is where feature engineering is critical in diagnostic pipelines [3]. Further, a hybrid system that incorporates the characteristics of the Deep Neural Network (DNN) with the classical ML classifier has improved classification accuracy even higher by extracting the low-level and high-level representations of the MRI data [4].

Besides traditional approaches, models based on DL, as well as explainable AI techniques, have become increasingly popular in brain tumor classification, especially when a large scale of samples can be trained on. Recent studies have considered utilizing hybrid architectures, such as Vision Transformer (ViT) and Gated Recurrent Units (GRU). These could use attention mechanisms to enhance the representation of the features and interpretability to make more reliable distinctions among different types of tumors, including glioma, meningioma, and pituitary tumors [5]. Such works depict the movement towards using hybrid methods of combining old-fashioned feature extractors with learnt representations. This is done to achieve a compromise between model efficiency, interpretability, and generalization in performance in a variety of different datasets, particularly in cases where the data available is limited or heterogeneous in nature [6].

Although this has been made possible, still there are challenges, such as redundant features, overfitting, and low interpretability. This limits the practical use of automated classifiers. Recent studies that combine feature selection algorithms and hybrid learning plans have the potential to overcome these drawbacks and make classification more reliable [7]. A middle-way type of hybrid feature-based ML structure can be used by taking advantage of the effectiveness of both designed features and data-driven learning in enhancing the classification accuracy, strength, and computational cost in multi-class tumor categorization tasks. This is the driving force behind the current research. It suggests an innovative hybrid feature-based ML framework to automatically and correctly classify brain tumors based on MRI images, wherein ideal feature extraction, selection, and classification methods are combined to fill the current gaps in automated diagnostic performance [8].

As proposed in this research, a hybrid feature-based ML system is suggested to be applied to automated brain tumor classification using brain MRI images. The suggested method would involve the combination of manually-crafted texture descriptors, such as Histogram of Oriented Gradients (HOG), with high-level semantic features learned under the ResNet-50 framework. This allows the proposed method to be robust in capturing both local and high-level tumor features. The framework is tested on two benchmark datasets that are publicly available, that is, the Figshare Brain Tumor MRI dataset and the Harvard Brain Tumor MRI dataset. This is done to test the strength and the generalization ability of the framework on various data distributions. Several ML classifiers, such as their variations as SVMs, LR, RF, and XGBoost, are used to verify the performance of the hybrid feature representation. The experimental findings prove that the suggested approach records a high classification rate and is better than various baseline setups. The rest of the study is structured as follows: section 3 outlines the proposed methodology including the preprocessing, feature extraction, and classification steps. Section 4 contains the discussion of the experimental findings and performance. Section 5 gives the discussion of the obtained results. Section 6 presents an ablation study of the contribution of each part and section 7 comprises the conclusion.

II. LITERATURE REVIEW

Timely and precise diagnosis of brain tumors is of paramount importance in clinical decision-making. This is because it directly affects the choice of treatment and a patient's survival rate. Furthermore, manual diagnosis with the help of an MRI scan is time-consuming and subject to inter-observer variation. This makes the application of automated techniques in medical imaging studies a necessity [9]. Recent literature indicates that ML and the hybrid feature-based models can potentially benefit successful classification using the combination of handcrafted and learned features. This is done to gain substantial improvements over the conventional approaches and minimize diagnostic errors in complicated neuroimaging contexts [3]. Furthermore, studies have demonstrated that the incorporation of hybrid methods, for instance, integrating deep feature detectors and traditional classifiers, may lead towards high accuracy and strength on MRI data. This has contributed to the increased significance of intelligent brain tumor systems in medical practice [10].

Conventional ML frameworks of brain tumor classification often use handcrafted methods of feature extraction, followed by the use of classification. This is because these methods are used to summarize image characteristics, such as texture and intensity patterns that are discriminative of the tumor type. Indicatively, the common texture descriptors, such as gray level co-occurrence matrix, local binary patterns, and histogram-based features were actively obtained on MRI scans to depict the tumor properties in order to undertake classification tasks using traditional classifiers, such as SVM, KNN, Naive Bayes, and decision trees (DTs) [11]. Experiments based on fusion of GLCM with LBP and then feature selection (e.g., PCA, information gain) and ML classifier have been found to be very accurate in separating tumorous and non-tumorous MRI images. This proves that the fusion of handcrafted features is effective in conventional methods. Although these traditional pipelines have performed well in various scenarios, their design and manual feature selection are limited by the fact that they may demand expert knowledge and manual adjustments. Furthermore, they may be both time-consuming and lacking in the ability to discover the true complexity of tumor structures in MRI data as compared to their deep component counterparts [3].

Recent ML-based systems of brain tumor classification primarily exploit the use of feature extraction and then the application of other traditional classifiers to determine the type of tumor given MRI images. These methods usually involve handcrafted characteristics, such as texture (e.g., Haralick or HOG) and classifiers, such as SVMs and KNN, which have shown competitive accuracy. These do not need as much computational expense as end-to-end DL systems. As an example, a hybrid feature engineering composed of five classifiers, such as SVMs and KNN, showed good performance on glioma, meningioma, and pituitary tumors. This highlights the effectiveness of feature-based ML pipelines [11]. Furthermore, extensive evaluations of hybrid methods express that enveloping DL in feature extraction and ML classification is assiduous each time compared to univariate ones and more so when the results of varied classifier outputs are merged or weighted. Such hybrid techniques have been highly accurate on large MRI data sets, and are better as generalisers compared to conventional handcrafted features themselves only [12]. Furthermore, detailed summaries of hybrid methods describe how DL with features extraction and ML classification has always shown better results as compared to single methods, including when multi-classifier outputs are averaged or weighted. These compound approaches have demonstrated great precision when used with considerable volumes of MRI data. Furthermore, these approaches enhance the generalization when used with conventional handcrafted characteristics alone [13].

The most recent studies in the area of brain tumor classification have represented the usefulness of hybrid structures using handcrafted and learned features to extract the complementary information contained in MRI images. As an example, Chowdhury et al. came up with a hybrid architecture. This incorporates both the EfficientNet B0 and SqueezeNet backbones along with handcrafted descriptors, including HOG, LBP, Gabor filters, and wavelet features, to make their designs more sensitive to texture. Moreover, at the same time, they have a higher classification accuracy in a computationally-efficient way [14]. Additionally, hybrid feature fusion methods have been demonstrated to enhance differences between types of tumors by utilizing both low-level features and high-level features that single method models may omit. Apart from this, numerous studies have also been based on feature concatenation and fusing with ensemble or ML classifiers to enhance robustness and high performance. By fusing the features generated by several pretrained CNNs (e.g., ResNet50 and DenseNet121) into a hybrid DL, a feature concatenation-based hybrid improved classification performance through richer feature representations [15].

Recent DL models, especially CNNs, have demonstrated extreme performance in automated brain tumor classification. This is because they can learn both hierarchical and discriminative features directly given MRI images, with their performance often being comparable to classic models (i.e. custom CNNs with an accuracy of >98% on multi class MRI datasets) without feature engineering (e.g. manual feature engineering) [16]. Several issues, however, associated with DL models include high computational cost, large annotated datasets, and overfitting, particularly when the amount of data is small, or the data is unbalanced. This limits clinical generalizability and interpretability in real-world scenarios [17]. In order to overcome these limitations, hybrid models that build on DL feature extractions and ML classifiers have been suggested, where CNNs are usually used to extract deep features, and ML algorithms (SVM or Extreme Learning Machines (ELM)) are used to classify data. An example is hybrid networks, such as CNN SVM and optimized DL ML ensembles. These have achieved improved performance metrics (e.g., higher recall and precision at a lower computational cost). Furthermore, these indicate that ML classifiers can adequately harness deep features to form high-quality tumor-type classifications at modest computational cost, which would otherwise be unachievable with pure DL models [18]. Such results suggest that the hybrid ML DL models could be a good future for brain tumor classification. This may help strike the right balance between the strength of deep networks and efficiency and flexibility of the conventional ML methods. Table I provides a comparative study of the recent methods of brain tumor classification.

TABLE I
COMPARATIVE ANALYSIS OF BRAIN TUMOR CLASSIFICATION APPROACHES

Ref	Year	Methodology	Dataset	Accuracy (%)
[19]	2023	ResNet50 with custom layers	REMBRANDT MRI dataset	96.95
[20]	2023	ResNet50 TL model	MRI Kaggle	96.00
[21]	2024	HOG features , SVM Classifier	MRI	90.27
[5]	2024	ViT , GRU, XAI Techniques	BrTMHD-2023 (MRI)	96.56
[22]	2024	Hybrid DL scheme combining deep feature extraction with ML classifiers (LR, SVM, RF, LightGBM)	MRI (multi-class)	98.90
[23]	2025	CNN for features , KNN Classification	Kaggle MRI	95.70
[13]	2025	Hybrid CNN, KNN Classifier	BraTS 2015 and 2017	96.25
[24]	2025	MobileNetV2 + DenseNet121 Ensemble + XAI and Decision Rules	Figshare MRI	91.70
[25]	2025	4-conv CNN with Dropout	MRI	95.86
[26]	2025	CNN Deep Features, SVM	Figshare MRI Dataset	96.00
[27]	2025	Basic CNN	Three Tumor Types (MRI)	94.39

III. METHODOLOGY

The current study intended to propose a hybrid feature-based intelligent ML approach for the automated classification of brain tumors. Fig. 1 indicates the methodology diagram of the proposed approach, which clarifies the various steps involved in the methodology. Initially, the preprocessing step is involved in enhancing the quality of the brain MRI images. This step ensures the removal of noise from the images so that the features can be extracted efficiently. Further, the discriminative features from the images can be extracted using a combination of handcrafted and intelligent approaches, as indicated by the use of HOG features along with the ResNet-50 architecture. This ensures the provision of accurate information regarding the tumor. Then, the feature output is subjected to classification using various intelligent techniques. Lastly, the performance of the output of the proposed approach is validated using evaluation metrics.

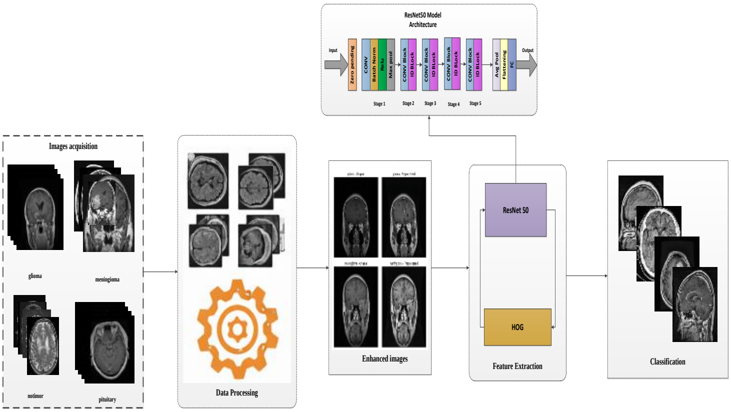


FIGURE 1. Methodology diagram of the proposed approach

A. DATA ACQUISITION

The first dataset employed in this research was the Brain Tumor MRI Dataset, which was collected from the Figshare platform, and is publicly accessible via the Kaggle platform. This dataset contained a total of 7,022 brain MRI images that were collected to analyze brain tumors automatically. These images contained various types of brain tumors as well as normal images, which were sufficient for the purpose of feature extraction and classification. The images in this dataset were provided in standard image formats with varying intensity distributions and structural details. Samples from the Figshare dataset are shown in Fig. 2.

The second dataset used in this study was the Brain Tumor Classification MRI Dataset which was obtained from Harvard Medical School, and is also available on Kaggle. This dataset consisted of 3,264 brain MRI images, including various types of tumors as well as non-tumor images. The Harvard dataset is commonly used in brain tumor classification research due to its high-quality MRI images and well-represented classes. The Harvard dataset has complementary properties to the Figshare dataset, which helps to enhance the generalization capability of the proposed framework. The sample images of the Harvard dataset are shown in Fig 3.

The merging of the datasets provides a vast resource that is imperative for the development and testing of the proposed brain tumor classification model, as indicated in Table II.

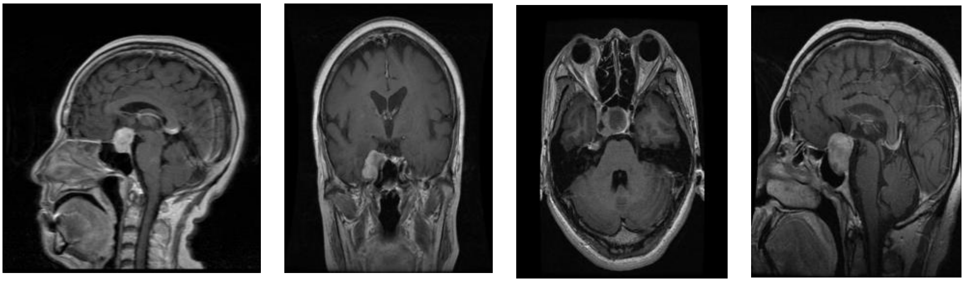


FIGURE 2. Sample images from the figshare dataset

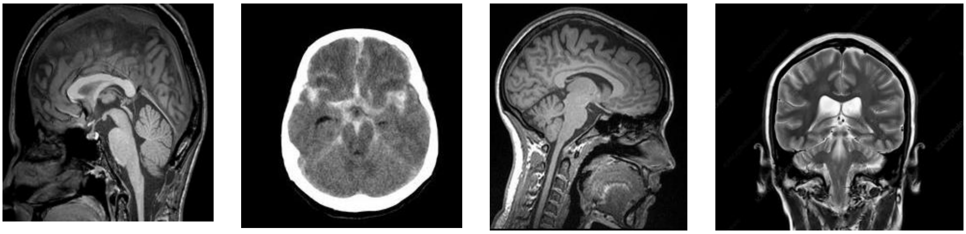


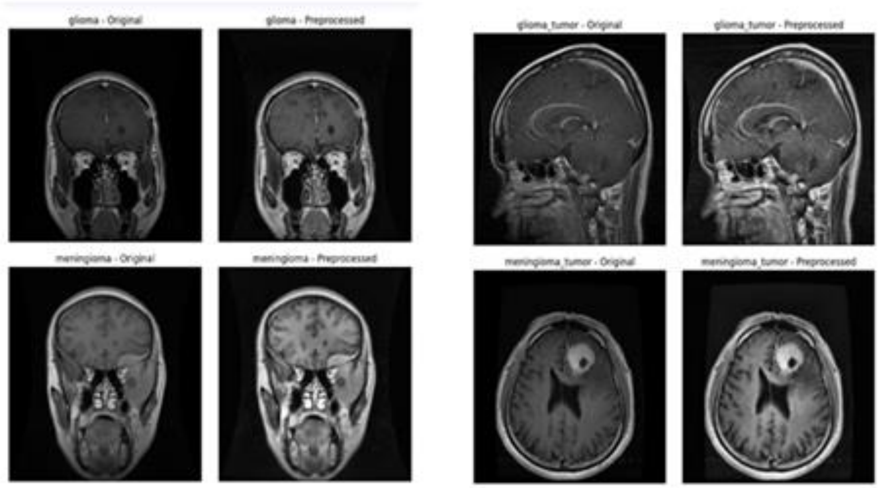
FIGURE 3. Sample images from the harvard dataset

TABLE II
DATA DESCRIPTION OF DATASETS

No	Dataset	Images
1	Figshare Brain Tumor MRI	7,022
2	Harvard Brain Tumor MRI	3,264
Total		10,286

B. PREPROCESSING

In the proposed approach, preprocessing is a key step for the purpose of getting the brain image ready in a suitable form to enable feature extraction or classification effectively within the system. Initially, the size of the image is set uniformly. This is done to ease the processing in the subsequent phases, when the handcrafted feature or the DL feature would require the image to be of a uniform size in order to ease the smooth functioning of the system in the required feature extraction or classification phases. Next in line is the image contrast enhancement through CLAHE preprocessing or the enhancement technique to highlight the region of the tumor in the image, effectively. Once the required contrast is established in the image through the aforementioned technique, the subsequent step would be the normalization of the image so that the pixels within the image operate within a uniform standard in the system by bringing uniformity in the standard of the pixels within the system. Additionally, in the context of making the neural network robust in the system, rotation, flip, scale, and translations are used effectively for the purpose of data augmentation within the system through an image generator for the purpose of utilizing the system effectively in the required context. The behavior of the model under different circumstances is demonstrated graphically in Figure 4.



(a) Figshare Dataset (b) Harvard Dataset

FIGURE 4. Sample Images after preprocessing from (a) figshare dataset (b) harvard dataset

C. FEATURE EXTRACTION

Feature extraction is a critical step in the proposed framework, aimed at representing MRI images in a form suitable for ML classifiers. This study employed a hybrid approach combining HOG and ResNet-50 to capture both low-level texture patterns and high-level semantic features from brain MRI images.

1) HISTOGRAM OF ORIENTED GRADIENTS (HOG)

HOG is a manually-designed feature descriptor that captures the local gradient orientation distribution of an image, which is quite useful for tumor texture and shape information. The basic steps involved in computing the HOG feature are gradient computation, orientation binning, and block normalization. Given an image, the gradients in horizontal and vertical directions are calculated as in equation (1).

$$G_x = I(x+1,y) - I(x-1,y)\,,$$

$$G_y = I\,(x,y+1) - I(x,y-1) \tag{1}$$

The gradient magnitude $M(x,y)$ and orientation $\theta(x,y)$ are then calculated as eqaution (2):

$$M(x,y) = \sqrt{G_x^2 + G_y^2}\,,\quad \theta(x,y) = \arctan\left(\frac{G_y}{G_x}\right) \tag{2}$$

The image is then divided into small cells, and for each cell, a histogram of gradient orientations is computed, weighted by the gradient magnitude. To enhance robustness to illumination and contrast, histograms are block-normalized using L2-norm, as illustrated in equation (3).

$$v \leftarrow \frac{v}{\sqrt{\|v\|_2^2 + \in^2}} \tag{3}$$

Where v represents the concatenated histogram vector and $\in$ is a small constant to avoid division by zero.

2) RESNET-50

To extract the high-level semantic features, a ResNet-50 deep CNN is used. ResNet-50 is a 50-layer residual network that proposes residual learning using skip connections. This enables the network to train a deep architecture without the problem of vanishing gradients.

As shown in equation (4), a residual block in ResNet-50 is defined as follows:

$$y = F(x, \{W_i\}) + x \tag{4}$$

Where x is the input to a residual block, $F(x, \{W_i\})$ represents the stacked convolutional layers, and y is the output of the block. Except for a single convolution and max-pooling, the ResNet-50 architecture follows four stages of residual blocks. This corresponds to 3 + 4 + 6 + 3 = 16 bottleneck blocks in total. Each block is similarly made up of three convolutions (1×1, 3×3, 1×1) with batch normalization and ReLU for each. Finally, it uses global average pooling into a fully connected layer to produce the feature vectors for classification. Figure 5 describes the architecture diagram.

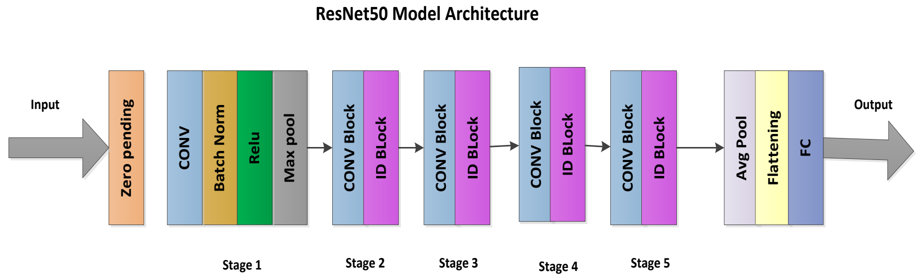


FIGURE 5. Model architecture of ResNet-50

By melding HOG features with ResNet-50 features, the method leverages both the local texture cues and deep layered representations that ramp up classifiers. This helps in distinguishing between inputs.

D. CLASSIFICATION

The current study used a carefully-chosen set of ML classifiers to distinguish reliably among the brain tumor types in both datasets. Based on strong theory and good steady performance on medical image analysis, the study employed Quadratic SVM, Gaussian SVM, Linear SVM, LR, RF, and XGBoost on the final decision. The input to these classifiers comes from hybrid feature vectors that blend handcrafted HOG features with deep features extracted from ResNet-50.

The variants of SVM are preferred due to their ability to handle high-dimensional feature spaces and complex boundaries of decisions. Specifically, Quadratic and Gaussian SVMs capture the non-linear relationships in feature space, while Linear SVMs provide computationally-efficient classification. LR acts as a probabilistic linear classifier that yields interpretable decision boundaries, thereby providing stable performance on medical data. RF presents an ensemble method that combines several DTs on the basis of generalization and overfitting reduction. This helps a lot in the diversity present in MRI features. XGBoost was selected because it is designed using a framework of gradient boosting. This, in turn, enhances performance in a progressive manner by minimizing the error in predictions.

These classifiers are trained and evaluated separately on both the Figshare and Harvard brain MRI datasets to test the generalizability and robustness of the hybrid framework. The results obtained from comparative performances prove that the chosen features are effective and support the overall approach for automated brain tumor classification.

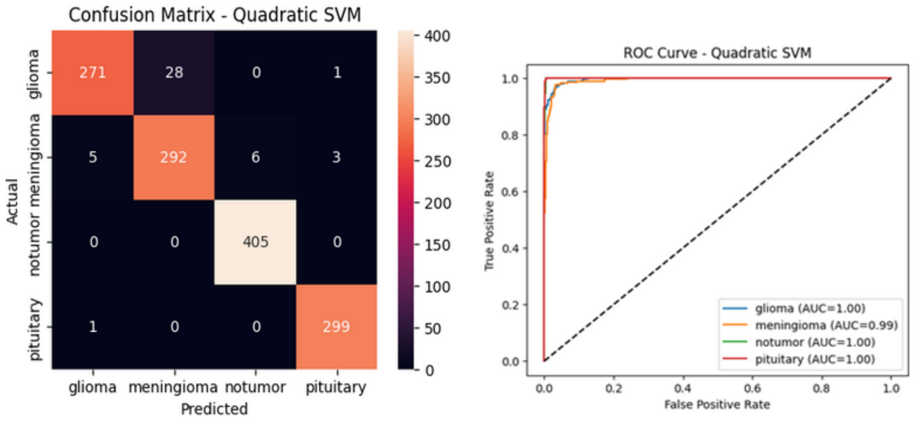
IV.RESULTS

In this section, the results of the experiment conducted with the help of the given hybrid feature-based framework of brain tumor classification are introduced. The model is tested on two-publicly available brain MRI datasets with the help of various ML classifiers on the performance of the model. To prove the effectiveness and strength of the offered approach, quantitative findings and graphics are presented.

A. *RESULTS ON FIGSHARE DATASET*

To test the proposed hybrid feature-based framework, the performance of the model was initially tested on the Figshare Brain MRI dataset using the selected ML classifiers. The experimental outcomes proved that the identified hybrid features are effective in extracting the discriminative tumor features. The Quadratic SVM was the most successful classifier with the highest accuracy in classifying images (97%). The Gaussian SVM and LR classifiers also performed very well with the accuracy of 96 and 95, respectively. Linear SVM also demonstrated an accuracy of 94%, which means that even linear decision boundaries can be useful in distinguishing the classes of tumors, provided powerful features are used. RF and XGBoost, as ensemble-based classifiers, achieved 91% and 92% of accuracy, which once again confirmed the usefulness of the suggested approach to feature extraction.

Table III presents the classification performance comparison on the Figshare dataset and the confusion matrix, and Roc curve of the best performing classifier (Quadratic SVM) is presented in the Fig. 6, which demonstrates the best classification ability. The confusion matrix and Roc curve of the best performing classifier (Quadratic SVM) are presented in the Fig. 7, which demonstrates the best classification ability.



(a) (b)

FIGURE 6. Performance of quadratic SVM (a) confusion matrix (b) ROC curve

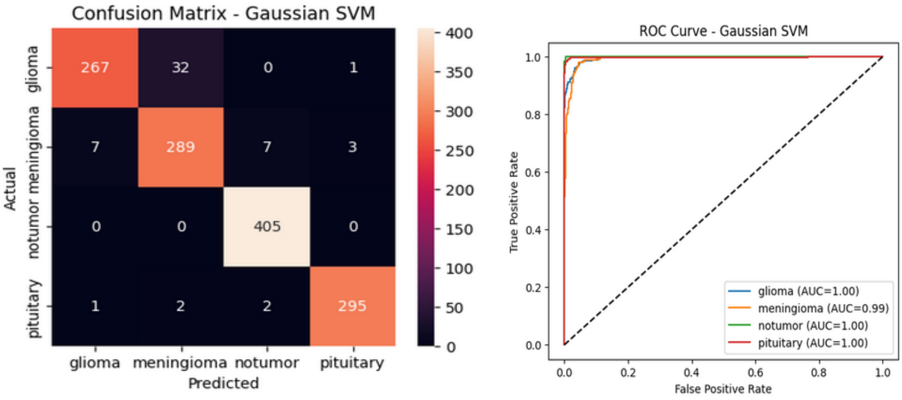
TABLE III

SUMMARY OF THE CLASSIFICATION REPORT FOR THE FIGSHARE CLASSIFIERS

Classifiers	Classes	Precision (%)	Recall (%)	F1-score (%)	Accuracy (%)
SVM	glioma	95	84	90	94
	meningioma	85	90	87	
	notumor	98	100	99	
	pituitary	96	98	97	
Random Forest (RF)	glioma	93	76	84	91
	meningioma	81	89	85	
	notumor	99	100	99	
	pituitary	92	97	94	
Linear SVM	glioma	95	86	90	94
	meningioma	88	90	89	
	notumor	98	100	99	
	pituitary	94	98	96	
Logistic Regression (LR)	glioma	95	90	92	95
	meningioma	90	91	90	
	notumor	98	100	99	
	pituitary	96	99	97	
Gaussian SVM	glioma	97	89	93	96
	meningioma	89	94	92	
	notumor	98	100	99	
	pituitary	99	98	98	
Quadratic SVM	glioma	98	90	94	97
	meningioma	91	95	93	
	notumor	99	100	99	
	pituitary	99	100	99	
XGBoost	glioma	92	81	97	92
	meningioma	82	87	84	
	notumor	98	100	99	
	pituitary	95	98	96	

B. RESULTS ON HARVARD DATASET

The suggested framework was also tested on the Harvard Brain MRI data to determine its ability to generalize to other data distributions. In comparison to the Figshare dataset, there was a significant difference in the performance of the classifiers in all cases. RF classifier had the best accuracy of 76%, followed by Quadratic SVM and Linear SVM with accuracy of 74% and 74%, respectively. The accuracy of LR and XGBoost stood at 73% and 72% respectively, whilst Gaussian SVM had an accuracy of 72% of accuracy.



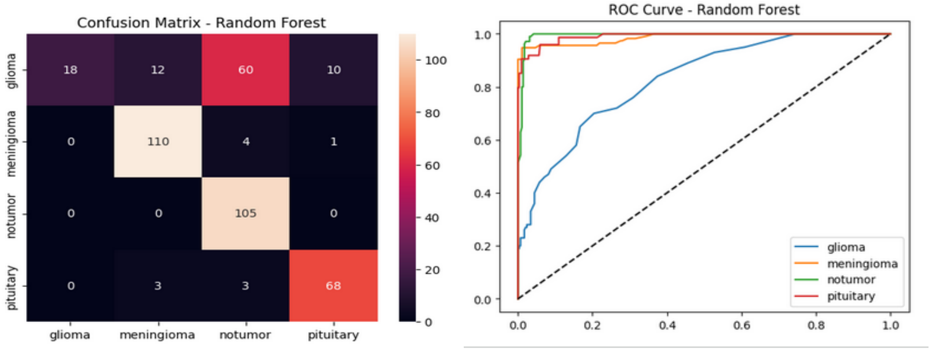
(a) (b)

FIGURE 7. Performance of Gaussian SVM (a) Confusion Matrix (b) ROC Curve

TABLE IV
SUMMARY OF THE CLASSIFICATION REPORT FOR THE HARVARD CLASSIFIER

Classifiers	Classes	Precision (%)	Recall (%)	f1-score (%)	Accuracy (%)
SVM	glioma	100	18	31	71
	meningioma	77	97	86	
	notumor	57	100	72	
	pituitary	98	59	74	
Random Forest (RF)	glioma	100	18	31	76
	meningioma	88	96	92	
	notumor	61	100	76	
	pituitary	86	92	89	
Linear SVM	glioma	86	18	30	74
	meningioma	78	97	86	
	notumor	62	100	77	
	pituitary	94	80	86	
Logistic Regression (LR)	glioma	90	18	30	73
	meningioma	70	97	81	
	notumor	67	100	80	
	pituitary	95	73	82	
Gaussian SVM	glioma	100	18	31	72
	meningioma	74	98	85	
	notumor	60	100	75	
	pituitary	98	65	78	
Quadratic SVM	glioma	95	18	30	74
	meningioma	67	98	80	
	notumor	70	100	83	
	pituitary	100	77	87	

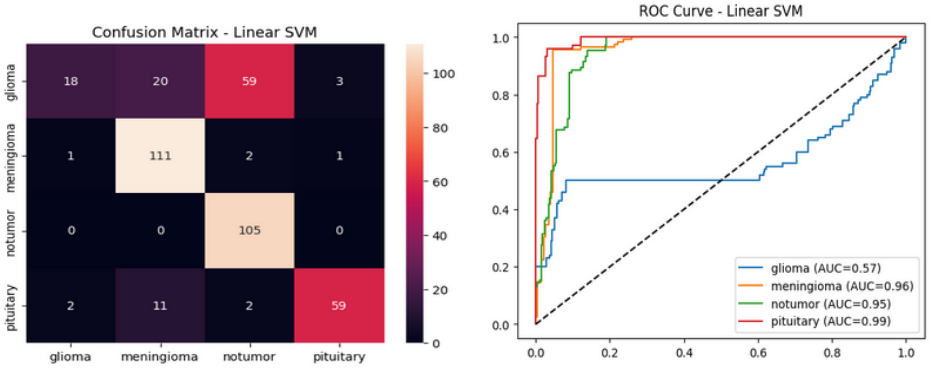
Classifiers	Classes	Precision (%)	Recall (%)	f1-score (%)	Accuracy (%)
XGBoost	glioma	90	18	30	73
	meningioma	81	96	88	
	notumor	59	100	74	
	pituitary	93	76	84	



(a) (b)

FIGURE 8. Performance of random forest (RF) (a) confusion matrix (b) ROC curve

The results suggest that the hybrid feature representation is efficient in datasets of different nature even though the overall performance decreased. The classifier-wise performance on the Harvard dataset is shown in detail in Table 4. Furthermore, the result visualization of the highest-performing classifier in this dataset can be found in Fig. 8, and Fig 9 revealed the classification behavior in more difficult conditions of data.



(a) (b)

FIGURE 9. Performance of Linear SVM (a) confusion matrix (b) ROC curve

V. DISCUSSION

The experiment outcomes confirm that the designed hybrid feature-based structure is effective in extracting discriminative data to classify brain tumors in both datasets. The greater performance of Quadratic SVM, especially the Figshare data, is evidence that the hybrid feature representation has an advantage of non-linear decision boundaries. Both handcrafted HOG features and deep features acquired by ResNet-50 allow the model to capture the local variations of texture as well as the high-level semantic features of the tumor regions, which is of great significance in improving the accuracy of classification. Their ability to work with high-dimensional feature spaces produced by hybrid feature extraction through the use of the SVM-based classifiers is exemplified by their consistent performance.

When a comparative analysis is conducted between the Figshare and Harvard datasets, it is possible to note that the classification performance is slightly different. The increased accuracy of the Figshare dataset can be explained by the fact that the classes are more or less equal, and the tumor patterns are clearer and therefore, allow the features to be learned easily. Conversely, the decrease in the performance on the Harvard dataset indicates that it is more complex, its classes may be imbalanced, and that the variability between classes may be higher. Nonetheless, the performance of classifiers, such as RF and Quadratic SVM did not vary, which is indicative that the suggested framework can be reliable in different circumstances. This disparity in performance highlights the need to consider automated medical diagnostic systems using a variety of datasets to determine their generalizability.

The strengths of the proposed approach can also be further underlined by the performance trends of the various classifiers. Ensemble-based algorithms, such as RF and XGBoost, showed a competitive result since they were able to combine decision boundaries and decrease overfitting. Linear SVM and LR were consistent and gave results that were stable and interpretable, thus showing the efficacy of the features extracted even when using linear classifiers. In general, the findings indicate that the hybrid feature extraction approach can increase the separability between tumor and non-tumor classes and thus, leads towards better performance of the classification task without the use of a single classifier. The obtained results prove that the given framework is reliable and generalized in terms of automated brain tumor classification and that it can be improved in the future by using larger datasets and developing more sophisticated strategies of feature fusion.

A. ABLATION STUDY

To assess the value of each of the elements of the proposed hybrid framework in automated brain tumor classification, an ablation study was carried out. To determine the influence of preprocessing, feature extraction, and hybrid feature fusion on the classification performance, varied experimental setups were tested on with different combinations of features, and the classification strategy was held constant. Firstly, classification based on handcrafted HOG features only showed that these features were good at capturing local texture and edge information. However, their total accuracy was poor because the features did not semantically represent any high-level information. The application of features obtained only with the help of ResNet-50 resulted in a better performance, and it was possible to note that the deep features can learn hierarchical and semantic features of tumors but at the cost of fine-grained texture features. The hybrid feature representation, which is a combination of HOG and ResNet-50 features, was uniformly the best in terms of classification performance regardless of the data used. This validates the fact that handcrafted and DL-based features are complementary. These findings confirm the fact that every element of the framework adds to the performance increase, and hybrid feature fusion is an important factor to increase the robustness and accuracy in brain tumor classification.

B. CONCLUSION

The current study presented a hybrid feature-based ML model that classified brain tumors automatically on two publicly-available MRI datasets, Figshare and Harvard. The framework currently combines handcrafted HOG characteristics with strong attributes obtained in the ResNet-50, that is, both the local texture and the high-level semantic features of tumor locations. As it was shown on an experimental basis, the hybrid feature approach, paired with a well-chosen set of classifiers including Quadratic SVM, Gaussian SVM, LR, RF, and XGBoost, yields high classification accuracy. Moreover, the Quadratic SVM can be selected as the best in the case of the Figshare dataset. The framework demonstrates a high level of performance when working with diverse datasets with different properties, which indicates its ability to be generalized and applied to clinical environments generally. In general, the presented methodology could be considered a valid, effective, and precise way of automated brain tumor detection. The modular nature of the suggested approach means that the proposed solution could be enhanced further by using larger volumes of data, more efficient means of feature fusion, and more successful classification approaches.

Author Contribution

Anam Naveed: conceptualization, methodology, data curation, formal analysis, visualization, and writing – original draft. **Mamoona Sadia:** review & editing, validation, and supervision.

Conflict of Interest

The authors of the manuscript have no financial or non-financial conflict of interest in the subject matter or materials discussed in this manuscript.

Data Availability Statement

Data supporting the findings of this study will be made available by the corresponding author upon request.

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REFERENCES

[1] F. F. Jiven and R. Rumini, "MRI classification of brain tumors using EfficientNetB0 feature extraction and machine learning methods," *J. Appl. Inform. Comput.*, vol. 9, no. 6, pp. 3394–3404, Dec. 2025, doi: https://doi.org/10.30871/jaic.v9i6.10363.

[2] M. Rasool, A. Noorwali, H. Ghandorh, N. A. Ismail, and W. M. S. Yafooz, "Brain tumor classification using deep learning: A state-of-the-art review," *Eng. Technol. Appl. Sci. Res.*, vol. 14, no. 5, pp. 16586–16594, Oct. 2024, doi: https://doi.org/10.48084/etasr.8298.

[3] K. Kumar, K. Jyoti, and K. Kumar, "Machine learning for brain tumor classification: Evaluating feature extraction and algorithm efficiency," *Discov. Artif. Intell.*, vol. 4, no. 1, 2024, Art. no. 112, doi: https://doi.org/10.1007/s44163-024-00214-4.

[4] H. Kibriya, R. Amin, A. H. Alshehri, M. Masood, S. S. Alshamrani, and A. Alshehri, "A novel and effective brain

tumor classification model using deep feature fusion and machine learning classifiers," *Comput. Intell. Neurosci.*, vol. 2022, Mar. 2022, Art. no. 7897669, doi: https://doi.org/10.1155/2022/7897669.

[5] M. M. Ahmed *et al.*, "Brain tumor detection and classification in MRI using hybrid ViT and GRU model with explainable AI in southern Bangladesh," *Sci. Rep.*, vol. 14, no. 1, Oct. 2024, Art. no. 22797, doi: https://doi.org/10.1038/s41598-024-71893-3.

[6] P. Parkhi et al., "Employing CNN features for automated brain tumor classification in MRI," *Int. J. Intell. Syst. Appl. Eng.*, vol. 12, no. 11, pp. 380–386, 2024.

[7] M. S. Ullah et al., "Brain tumor classification from MRI scans: A framework of hybrid deep learning model with Bayesian optimization and quantum theory-based marine predator algorithm," *Front. Oncol.*, vol. 14, 2024, Art. no. 1335740, doi: https://doi.org/10.3389/fonc.2024.1335740.

[8] M. Ghorbian, S. Ghorbian, and M. Ghobaei-Arani, "A comprehensive review on machine learning in brain tumor classification: Taxonomy, challenges, and future trends," *Biomed. Signal Process. Control*, vol. 98, 2024, Art. no. 106774, doi: https://doi.org/10.1016/j.bspc.2024.106774.

[9] S. E. Nassar et al., "A robust MRI-based brain tumor classification via a hybrid deep learning technique," *J. Supercomput.*, vol. 80, no. 2, pp. 2403–2427, 2024, doi: https://doi.org/10.1007/s11227-023-05549-w.

[10] Q. U. A. Ishfaq et al., "Automatic smart brain tumor classification and prediction system using deep learning," *Sci. Rep.*, vol. 15, no. 1, 2025, Art. no. 14876, doi: https://doi.org/10.1038/s41598-025-95803-3.

[11] B. Pattanaik et al., "Brain tumor magnetic resonance images classification based machine learning paradigms," *Contemp. Oncol.*, vol. 26, no. 4, pp. 268–274, 2022, doi: https://doi.org/10.5114/wo.2023.124612.

[12] J. Kang, Z. Ullah, and J. Gwak, "MRI-based brain tumor classification using ensemble of deep features and machine learning classifiers," *Sensors*, vol. 21, no. 6, Mar. 2021, Art. no. 2222, doi: https://doi.org/10.3390/s21062222.

[13] R. Missaoui et al., "Advanced deep learning and machine learning techniques for MRI brain tumor analysis: A review," *Sensors*, vol. 25, no. 9, 2025, Art. no. 2746, doi: https://doi.org/10.3390/s25092746.

[14] M. S. Chowdhury et al., "Squeezed-Eff-Net: Edge-computed boost of tomography-based brain tumor classification leveraging hybrid neural network architecture," *arXiv*, 2025. [Online]. Available: https://arxiv.org/abs/2512.07241.

[15] S. C. Gupta, S. Vijayvargiya, and V. Bhattacharjee, "Role of feature diversity in the performance of hybrid models—An investigation of brain tumor classification from brain MRI scans," *Diagnostics*, vol. 15, no. 15, 2025, Art. no. 1863, doi: https://doi.org/10.3390/diagnostics15151863.

[16] M. A. Khan and R. B. Z. Auvee,

"Comparative analysis of resource-efficient CNN architectures for brain tumor classification," in Proc. 27th Int. Conf. Comput. Inf. Technol. (ICCIT), Dhaka, Bangladesh, Dec. 2024.

[17] N. Netshamutshedzi et al., "A systematic review of the hybrid machine learning models for brain tumour segmentation and detection in medical images," *Front. Artif. Intell.*, vol. 8, 2025, Art. no. 1615550, doi: https://doi.org/10.3389/frai.2025.1615550.

[18] M. Nahiduzzaman et al., "A hybrid explainable model based on advanced machine learning and deep learning models for classifying brain tumors using MRI images," *Sci. Rep.*, vol. 15, no. 1, 2025, Art. no. 1649, doi: https://doi.org/10.1038/s41598-025-85874-7.

[19] A. K. Sharma et al., "Brain tumor classification using the modified ResNet50 model based on transfer learning," *Biomed. Signal Process. Control*, vol. 86, 2023, Art. no. 105299, doi: https://doi.org/10.1016/j.bspc.2023.105299.

[20] N. A. Zebari et al., "Enhancing brain tumor classification with data augmentation and DenseNet121," *Acad. J. Nawroz Univ.*, vol. 12, no. 4, pp. 323–334, 2023, doi: https://doi.org/10.25007/ajnu.v12n4a1985.

[21] C. K. K. Reddy et al., "A fine-tuned vision transformer based enhanced multi-class brain tumor classification using MRI scan imagery," *Front. Oncol.*, vol. 14, 2024, Art. no. 1400341, doi: https://doi.org/10.3389/fonc.2024.1400341.

[22] Z. Wang et al., "A hybrid deep learning scheme for MRI-based preliminary multiclassification diagnosis of primary brain tumors," *Front. Oncol.*, vol. 14, 2024, Art. no. 1363756, doi: https://doi.org/10.3389/fonc.2024.1363756.

[23] S. Iftikhar et al., "Explainable CNN for brain tumor detection and classification through XAI-based key features identification," *Brain Inform.*, vol. 12, no. 1, 2025, Art. no. 10, doi: https://doi.org/10.1186/s40708-025-00253-2.

[24] M. Filvantorkaman et al., "Fusion-based brain tumor classification using deep learning and explainable AI, and rule-based reasoning," *arXiv*, 2025. [Online]. Available: https://arxiv.org/abs/2508.06891

[25] V. R. Srinivas and R. Parvathi, "Explainable AI-driven MRI-based brain tumor classification: A novel deep learning approach," *Front. Artif. Intell.*, vol. 8, 2025, Art. no. 1700214, doi: https://doi.org/10.3389/frai.2025.1700214.

[26] M. Ottoni, A. Kasperczuk, and L. M. Tavora, "Machine learning in MRI brain imaging: A review of methods, challenges, and future directions," *Diagnostics*, vol. 15, no. 21, 2025, Art. no. 2692, doi: https://doi.org/10.3390/diagnostics15212692.

[27] Y. Wong et al., "Brain tumor classification using MRI images and deep learning techniques," *PLoS ONE*, vol. 20, no. 5, May 2025, Art. no. 0322624, doi: https://doi.org/10.1371/journal.pone.0322624.