**Journal of Online Engineering Education**
**ISSN: 2158-9658 Volume: 17 Issue: 1**
**Article Received**: 26 January 2026 **Revised**: 18 March 2026 **Accepted**: 10 April 2026

# Quantum-Inspired Adaptive Feature Fusion for Highly Accurate Brain Tumor Classification in MRI Images

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**Abstract:** Accurate brain tumor classification from magnetic resonance imaging (MRI) is crucial for early diagnosis and effective treatment planning. Many deep learning models rely on simple feature concatenation, which limits the use of complementary information from different feature types. This work proposes a Quantum-Inspired Adaptive Feature Fusion (QIAFF) method integrated with deep learning for improved brain tumor classification. MRI images are preprocessed using median and anisotropic diffusion filtering to enhance image quality. Handcrafted features such as HOG and texture descriptors, along with CNN deep features, are extracted to represent tumor characteristics. Quantum-inspired probability principles are used to assign adaptive weights to each feature set through a rotation-based update rule. The weighted features are fused into an optimal representation before classification. A deep neural network then performs tumor classification using the fused features. Experimental results show improved accuracy, precision, recall, and F1-score compared to conventional fusion and deep learning methods. The proposed approach enhances feature discrimination and generalization, making it effective for reliable brain tumor detection from MRI images.

**Keywords:** Brain Tumor Classification, Quantum-Inspired Adaptive Feature Fusion, Deep Learning, HOG Features, Texture Features, Anisotropic Diffusion Filtering, Feature Fusion, Medical Image Analysis.

## I. INTRODUCTION

The human brain is one of the most complex and vital organs of the body, responsible for controlling all physiological and cognitive functions. Abnormal growth of cells within the brain leads to the formation of tumors, which can severely affect neurological activities and may become life-threatening if not detected at an early stage [1]. Brain tumors such as glioma, meningioma, and pituitary tumors exhibit diverse structural patterns and growth characteristics, making accurate diagnosis a challenging task for radiologists. Early identification and classification of these tumors play a significant role in planning appropriate treatment strategies and improving patient survival rates.

Magnetic Resonance Imaging (MRI) is widely regarded as the gold standard for brain tumor diagnosis due to its superior soft-tissue contrast and non-invasive nature. However, manual analysis of MRI scans is time-consuming and subject to inter-observer variability. In recent years, deep learning techniques, particularly convolutional neural networks, have demonstrated remarkable performance automated

brain tumor classification. These models can learn complex patterns from MRI data, but their effectiveness is often limited by the way features are combined and utilized during the learning process.

Most existing approaches rely on direct feature concatenation or static fusion of handcrafted and deep features, which may fail to capture the complementary information present in different feature representations. Handcrafted features such as Histogram of Oriented Gradients (HOG) and texture descriptors capture structural and spatial information, while deep features extracted from CNNs provide high-level semantic representation [2]. Without an intelligent fusion strategy, the potential benefits of these diverse feature sets remain underutilized, leading to reduced classification performance and generalization capability.

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To address these limitations, this work introduces a Quantum-Inspired Adaptive Feature Fusion (QIAFF) mechanism integrated with deep learning for brain tumor classification from MRI images. The proposed method employs quantum probability concepts such as superposition and rotation-based weight updating to dynamically assign importance to multiple feature sets before classification. By adaptively fusing handcrafted and deep features into an optimal representation, the model enhances feature discrimination and improves classification accuracy [3]. This quantum-inspired fusion strategy, combined with deep learning, provides a robust framework for reliable and highly accurate brain tumor detection.

## II. RELATED WORKS

Recent advancements in medical image analysis have significantly improved automated brain tumor classification using machine learning and deep learning techniques. Traditional machine learning models such as Support Vector Machines (SVM), K-Nearest Neighbors (KNN), Random Forest, and Naïve Bayes have been widely used with handcrafted features like Histogram of Oriented Gradients (HOG), Local Binary Patterns (LBP), and Gray Level Co-occurrence Matrix (GLCM) [4]. Although these methods achieved moderate accuracy, their performance largely depends on effective feature extraction and selection, and they often struggle with high-dimensional MRI data and class imbalance issues.

With the emergence of deep learning, Convolutional Neural Networks (CNNs) have become the dominant approach for brain tumor classification and segmentation. Architectures such as U-Net, ResNet, and hybrid CNN-based models have demonstrated improved accuracy by automatically learning hierarchical feature representations from MRI images. Transfer learning and data augmentation techniques have further enhanced performance [13], particularly when dealing with limited medical datasets. However, many deep learning models rely solely on deep features and do not effectively integrate complementary handcrafted features that may capture additional structural and texture information.

To overcome these challenges, several hybrid approaches have been proposed that combine handcrafted and deep features. Feature fusion techniques, including early fusion, late fusion, and simple concatenation, have been used to improve classification performance. While these methods provide some improvement, they typically employ static weighting schemes that do not adapt to variations in tumor characteristics across different images. As a result, the full potential of multi-feature integration remains underexploited.

More recently, quantum-inspired optimization algorithms have been introduced in medical image analysis to enhance feature selection and parameter tuning. These approaches utilize quantum probability principles to improve search efficiency and avoid local optima. Although quantum-inspired methods have shown promising results, most studies focus on optimization rather than adaptive feature fusion within deep learning frameworks [5]. Therefore, there remains a need for a dynamic and intelligent fusion strategy that can effectively integrate diverse feature representations for improved brain tumor classification accuracy.

Accurate brain tumor classification from MRI images remains challenging due to variations in tumor size, shape, intensity, and imaging conditions. Although deep learning models achieve promising results, many existing methods rely on either handcrafted features or deep features alone, limiting their ability to capture complementary information [14]. Hybrid approaches often use simple concatenation or fixed-weight fusion, which fails to adapt to image-specific characteristics and may reduce classification performance. Moreover, there is no dynamic mechanism to determine the relative importance of different feature representations during training. To address these limitations, the proposed Quantum-Inspired Adaptive Feature Fusion method introduces a probabilistic weight updating strategy that adaptively combines multiple feature sets, enabling improved feature discrimination and enhanced classification accuracy for brain tumor detection from MRI images [15].

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## III. PROPOSED WORK

### *Problem Identification*

Accurate brain tumor classification from MRI images remains challenging due to variations in tumor size, shape, intensity, and imaging conditions. Although deep learning models achieve promising results, many existing methods rely on either handcrafted features or deep features alone, limiting their ability to capture complementary information [6]. Hybrid approaches often use simple concatenation or fixed-weight fusion, which fails to adapt to image-specific characteristics and may reduce classification performance. Moreover, there is no dynamic mechanism to determine the relative importance of different feature representations during training. To address these limitations, in the

proposed Quantum-Inspired Adaptive Feature Fusion method introduces a probabilistic weight updating strategy that adaptively combines multiple feature sets, enabling improved feature discrimination and enhanced classification accuracy for brain tumor detection from MRI images.

### *Kaggle Dataset*

The MRI dataset used in this study is obtained from **Kaggle** and consists of 3264 T1-weighted, contrast-enhanced brain MRI images categorized into four classes: normal brain, meningioma, pituitary tumor, and glioma. The dataset includes 500 normal images, 937 meningioma images, 901 pituitary tumor images, and 926 glioma images. These labeled images are widely used for supervised deep learning research and provide sufficient diversity for training and validating automated brain tumor classification models. The dataset contains variations in tumor size, shape, and location, which helps improve the robustness of the proposed model. Additionally, the images are collected under different imaging conditions, supporting effective evaluation of model generalization.

### *Image Acquisition and Preprocessing*

The MRI images are loaded using the OpenCV library for efficient preprocessing. Each image is converted into grayscale format to reduce computational complexity while preserving structural details [7]. The images are resized to a uniform dimension of 200 × 200 pixels to ensure consistency in input representation. The processed images are stored in feature array $X$, and their corresponding labels are stored in target array $Y$. This normalization ensures compatibility with the deep learning model and prevents dimensional inconsistencies during training.

### *Data Augmentation*

To improve model generalization and reduce overfitting, data augmentation techniques are applied to the training dataset. Transformations such as rotation, horizontal and vertical flipping, shifting, zooming, and scaling are used to artificially increase dataset diversity. These augmentations simulate real-world variations in tumor orientation, size, and imaging conditions. By enhancing the variability of training samples, the model becomes more robust to unseen MRI scans and class imbalance problems.

### *Anisotropic Diffusion Filtering (ADF)*

Anisotropic Diffusion Filtering is used to further refine MRI images by selectively smoothing homogeneous regions while preserving tumor boundaries [8]. The diffusion process is controlled by gradient-based parameters to avoid blurring significant anatomical structures. ADF enhances contrast between tumor and normal tissues, making feature extraction more effective for classification tasks.

### *Multi-Feature Extraction*

To capture comprehensive tumor characteristics, multiple feature representations are extracted. Histogram of Oriented Gradients (HOG) is used to capture shape and edge information. Texture features such as GLCM or LBP are extracted to represent spatial intensity variations. In addition, deep features are obtained from intermediate layers of a Convolutional Neural Network (CNN) to capture high-level semantic information. These diverse feature sets provide complementary information about tumor structures.

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***Quantum-Inspired Adaptive Feature Fusion (QIAFF)***

The proposed QIAFF framework begins by extracting multiple feature sets from MRI images, including handcrafted texture features and deep learning-based representations. Instead of directly concatenating these features, each feature group is assigned an adaptive probabilistic weight. These weights are initialized under a quantum-inspired superposition principle, allowing all feature groups to contribute equally at the initial stage without bias. This initialization ensures balanced participation of diverse feature representations before optimization begins [9].

while performing the learning phase, the simulated probabilistic weights are iteratively optimized with a quantum-inspired rotation-based update mechanism that is based on classification loss. The update process changes the contribution of each feature group based on how well it predicts [10]. Feature sets that improve the accuracy of classification get more weight, while features that are not very helpful get less weight over time. This adaptive updating strategy works like quantum state evolution and keeps normalization constraints in place to make sure that convergence stays stable.

Furthermore, the optimally designed probabilistic weights [11] are used to produce the fused feature vector, which is a weighted combination of all the feature groups. This adaptive fusion mechanism advances the capability to tell a distinction between things by focusing on the most important features for classification. As a result, QIAFF makes brain tumor detection tasks more accurate, reliable, and able to work with new data.**Deep Learning-Based Classification**

The optimally fused feature representation is fed into a deep neural network classifier for final tumor categorization [12]. The network learns discriminative patterns from the adaptively fused features to classify MRI images into normal or tumor classes. The integration of quantum-inspired adaptive fusion with deep learning enhances feature discrimination, improves classification accuracy, and strengthens model generalization capability.

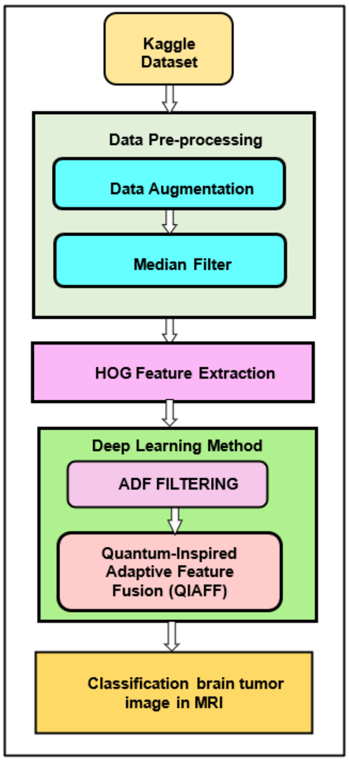


Fig. 3.1 Flow Diagram of Quantum-Inspired Adaptive Feature Fusion (QIAFF) Method

Proposed QIAFF Algorithm for Brain Image Classification in MRI

| | |
|---|---|
| ***Step 1:*** | Input Kaggle MRI dataset of size Height × Width ×Channels.Apply median filtering and anisotropic diffusion filtering.<br>Store preprocessed images and generate initial feature maps $F_i$.This ensures noise reduction and uniform image representation before feature extraction.. |
| ***Step 2:*** | Extract multiple feature sets from MRI images: HOG features $F_1$, texture features $F_2$, and CNN deep features $F_3$.Each feature type captures complementary structural, spatial, and semantic tumor characteristics. |
| ***Step 3:*** | Initialize quantum-inspired weight vector<br>W=[w1,w2,w3],∑wi=1<br>representing the contribution of each feature set.The weights indicate the relative importance of each feature group. |
| ***Step 4:*** | Extract best feature subset F_opt from best individual |
| ***Step 5:*** | Compute fused feature representation<br>$$F_{fused} = w_1F_1 + w_2F_2 + w_3F_3$$<br>*The adaptive fusion integrates handcrafted and deep features into a single optimized representation.* |
| ***Step 6:*** | Feed $F_{fused}$ into the deep neural network classifier.<br>*The classifier learns discriminative patterns from the fused features.* |
| ***Step 7:*** | Evaluate classification loss and accuracy.<br>*Performance metrics guide the adaptive update of feature weights.* |
| ***Step 8:***<br><br>***Step 9 :*** | Update weights using quantum-inspired rotation rule:<br>$$\boldsymbol{w_i^{new}} \frac{\boldsymbol{w_i + \theta}}{\sqrt{(\boldsymbol{w_i + \theta}).^2 + (\boldsymbol{1 - w_i^2})}}$$<br>where $\theta$is adjusted based on loss.<br>*This mimics quantum state evolution to dynamically refine feature importance.*<br>Normalize updated weights so that $\sum w_i = 1$.<br>*Normalization maintains probabilistic consistency of the weight vector.* |
| ***Step 10:*** | Recompute fused features using updated weights.<br>*The refined fusion enhances discriminative capability for classification* |

| | |
|---|---|
| ***Step 11:*** | Repeat Steps 6–10 until convergence or maximum epochs reached. *The iterative process ensures optimal adaptive fusion is achieved.* |
| ***Step 12:*** | End |

## IV. RESULTS AND DISCUSSION

The proposed Quantum-Inspired Adaptive Feature Fusion method addresses the common challenges associated with limited and imbalanced medical MRI datasets by improving the robustness and learning capability of deep learning models. By dynamically assigning adaptive weights to multiple complementary feature sets, the method reduces dependency on any single feature representation and minimizes the risk of overfitting. The quantum-inspired fusion strategy enhances the discriminative power of features before classification, allowing the model to generalize effectively even with scarce training data. This adaptive learning approach significantly improves the accuracy and reliability of brain tumor detection and classification from MRI images.

The proposed Quantum-Inspired Adaptive Feature Fusion (QIAFF) method is highly effective in handling complex tumor structures, irregular shapes, and subtle lesion regions in MRI images due to its ability to intelligently combine multiple complementary feature representations. By dynamically adjusting the contribution of handcrafted and deep features, the method captures both fine structural details and high-level semantic information. The adaptive fusion process enhances feature utilization before classification, while the deep learning architecture ensures efficient learning of discriminative patterns. This integrated approach reduces information loss, improves feature representation, and strengthens the overall accuracy and reliability of brain tumor classification.

***Precision***

Precision specifically measures how many of the items identified as positive are actually correct. The precision of preoperative diagnosis of brain tumor is crucial for deciding the pertinent operative strategy and for providing adequate information to the patient.

$$\textit{Precision} = \frac{TP}{TP+FP} \quad \text{---------}(4.1)$$

***Recall***

Recall in brain tumor detection measures how well a system can identify all actual tumor cases. It indicates the ability of the system to detect tumors without missing them.

$$\textit{Recall} = \frac{TP}{TP+FN} \quad \text{---------}(4.2)$$

***F1-Score***

It combines precision and recall into a single score. In brain tumor detection using medical imaging, the F1-score is commonly used to evaluate the performance of classification or segmentation models. In brain tumor

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diagnosis, this balance is important because missing a tumor (false negative) can delay treatment, while incorrectly detecting a tumor (false positive) may lead to unnecessary medical procedures.

$$\boldsymbol{F1 - Score = \frac{2X(\ Precision\ X\ Recall)}{Precision\ + Recall}} \text{ ----(4.3)}$$

***Accuracy***

Accuracy quantifies the overall accuracy of classification. The ratio of the total number of positive forecasts made by the model to the extent of genuine positive expectations. It illustrates the model's ability to accurately identify positive events while simultaneously restricting the misclassification of negative cases as certain.

$$\boldsymbol{Accuracy = \frac{TP+TN}{FP+FN}} \qquad \text{----- (4.4)}$$

The proposed procedure produces superior DSC outcomes relative to existing methods as shown in figure. The loss and accuracy for both the quantum and classical models are computed across 100 epochs for the training and validation datasets.

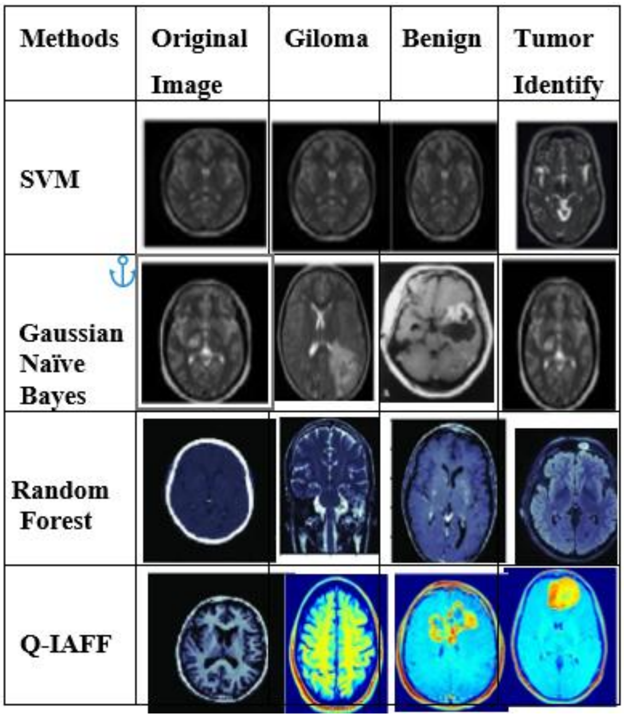


Fig.4.1 Comparative Analysis of Brain Tumor Classification Methods

Common brain tumor types include glioma, meningioma, and pituitary tumors, each exhibiting distinct structural patterns and growth characteristics in MRI images. Accurate identification of these tumors is essential for effective diagnosis and treatment planning. Brain tumor diagnosis is typically confirmed through pathological examination after imaging techniques such as MRI suggest abnormal tissue growth. The tissue sample obtained through biopsy or surgery is analyzed to determine the tumor type, grade, and cellular behavior.

In automated brain tumor classification, MRI images must be carefully preprocessed and analyzed to distinguish between normal and abnormal regions. This requires effective extraction and utilization of multiple feature representations that capture structural, textural, and semantic information from the images. Traditional approaches often rely on simple feature fusion or static weighting, which may not fully exploit the complementary information present in different feature sets.

The proposed Quantum-Inspired Adaptive Feature Fusion (QIAFF) method addresses this limitation by dynamically combining handcrafted and deep features using quantum probability principles. Instead of selecting features, the method adaptively assigns importance to each feature group through a rotation-based weight updating mechanism. This intelligent fusion enhances feature discrimination before classification. The fused feature representation is then used by a deep learning classifier to accurately identify tumor types from MRI images. This approach improves classification performance, supports reliable diagnosis, and assists medical professionals in making informed treatment decisions.

| Methods | Precision | Recall | F1-Score | Accuracy |
| --- | --- | --- | --- | --- |
| SVM | 92.4 | 93.8 | 92.4 | 91.9 |
| Gaussian Naïve Bayes | 92.3 | 92.3 | 93.6 | 92.2 |
| Radom Forest | 94.8 | 93.7 | 94.6 | 94.3 |
| QIAFF (Proposed) | 97.2 | 97.5 | 97.3 | 98.4 |

Table 4.2 Comparative table of tumor methods **Classification**

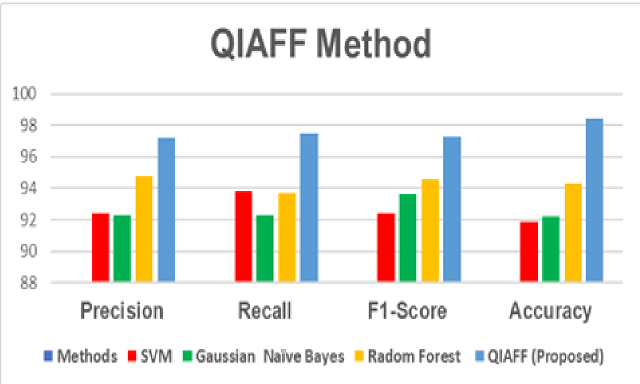


**Fig.4.3 Comparative chart of tumor methods Classification**

The comparison results show that the proposed method QIAFF (Proposed) outperforms all existing methods across every evaluation metric. It achieves the highest Precision (97.2%), Recall (97.5%), F1-Score (97.3%), and Accuracy (98.4%), indicating superior classification performance and better balance between true positive detection and error reduction. The chart clearly highlights this improvement, as QIAFF consistently records higher values than SVM, Gaussian Naïve Bayes, and Radom Forest, demonstrating its effectiveness and reliability.

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## V. CONCLUSION

The proposed work, QIAFF (Proposed), primarily contributes to brain tumor detection by integrating hybrid feature selection strategies and advanced classification techniques. It combines multiple feature extraction methods through feature fusion to capture rich MRI texture information. The approach employs the QIAFF mechanism along with a stacking ensemble classifier to improve the accuracy of tumor classification. By effectively selecting optimal features and enhancing classification performance, the proposed method accurately identifies the presence and precise location of brain tumors from MRI images.

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