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QUANTUM BASED BINARY BAT DEEP LEARNING METHOD FOR BRAIN TUMOR CLASSIFICATION IN MRI IMAGES

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Abstract

In order to accurately diagnose, treat, and manage a variety of diseases, it is essential to have medical images that are stored, analyzed, and transmitted in a manner that is both efficient and dependable. Numerous studies in this sector have concentrated on the utilization of quantum and quantum-inspired algorithms to boost the performance of traditional medical image processing procedures. The model that has been proposed is an mix of quantum-based algorithms and algorithms inspired by nature, and it incorporates the more hopeful aspects of both types of algorithms. By utilizing the quantum-based binary bat algorithm, also known as q-BBA, the proposed model has been successful in reducing dimensionality, which refers to aspects that are not necessary. QBBA achieved superior results than its conventional algorithms. This was discovered after comparing the performance of QBBA with that of its conventional methods. The QBBA algorithm emerges as a notable algorithm due to its enhanced noise immunity. The proposed Quantum-based Binary Bat method has the potential to be applied in the detection of brain tumors.

I. INTRODUCTION

The human brain is the organ that is both the most vital and the most complex in the human body. The functions of other organs are under its supervision, and it is responsible for the processing of billions of cells in the central nervous system [1]. In spite of the fact that abnormal tumors and lesions in the brain are extremely uncommon, they are nevertheless capable of causing significant consequences. It is possible for unregulated cell proliferation to result in the development of brain tumors, which are typically lethal. Magnetic resonance imaging scans of normal and abnormal brain tissues in order to highlight the morphological changes that are associated with brain cancers [6]. Because these tumors are associated with high rates of morbidity and mortality around the globe, they pose a significant threat to the lives of people.

Magnetic resonance imaging is considered the gold standard for finding and classifying brain cancers because of its superior soft-tissue contrast resolution and the fact that it does not involve any external invasive procedures. The majority of the material that is currently being published focuses on algorithmic improvements in this field [8]. This is despite the fact that recent advancements in deep learning and machine learning have greatly boosted the accuracy of tumor classification from MRI images.

The countries are currently experiencing a severe shortage of caregivers, with approximately two thousand oncologists being responsible for the treatment of nearly ten million patients, according to a report that was published in 2018 [4]. It is impossible for the medical community to develop a standardized approach to the segmentation of brain tumors because of the existence of anomalies. A precise diagnosis and evaluation of brain tumors can be accomplished by the utilization. This research endeavor is geared toward the utilization of magnetic resonance imaging for the purpose of systematically identifying brain malignancies [9].

In addition to being the principal component of the cavity of the neural tube, the human brain and spinal cord collaborate to form the central nervous system, which is an essential component of the nervous system. As a result of its great resolution and the fact that it does not require the use of radiation, magnetic resonance imaging has become a significant diagnostic method for brain cancers. In spite of the enormous progress that has been made in medicine, early detection and adequate treatment continue to be limited. This has led to increased case fatality rates and a major impact on disability-adjusted life years.

There are variations in the burden across the globe based on geographical location and demographic characteristics such as age, gender, and socioeconomic status. High-income countries have higher cancer incidence rates than low-income countries do. This is because high-income countries have better diagnostic capabilities, environmental exposures, genetic predispositions, lifestyle differences, and comprehensive cancer registration systems [10]. Low- and middle-income countries, on the other hand, are likely to underestimate their burden due to the limited availability of healthcare facilities, restricted access to neuroimaging, poor pathology services, and disconnected cancer registration systems. This underreporting creates challenges when attempting to correctly compare the burdens of sickness across different socioeconomic circumstances and may contribute to the concealment of a more serious global problem than is currently being recorded.

II. RELATED WORKS

The use of neuroimaging classification techniques has grown significantly in recent years due to the need to improve the accuracy and effectiveness of brain tumor classification. These state-of-the-art methods are specifically designed to enhance overall classification performance. This article looks at a number of convolutional neural network classification architectures used in neuroimaging and techniques for categorizing images of brain tumors. It focuses on the models, datasets, advantages, and disadvantages of recent important studies on brain tumor classification [11].

The collection should contain MRI images of three distinct brain areas, including the area where the tumor is visible. The application of DL and ML in medical imaging, particularly for the identification of brain malignancies, has significantly advanced during the last ten years. Due to the intricacy and diversity of brain tumors, improving patient outcomes requires an accurate and timely diagnosis. Magnetic resonance imaging is the most widely used imaging modality due to its better soft tissue contrast and non-invasiveness [14]. The manual processing of MRI data by radiologists is a normal procedure, although it is subject to human error and variability. Consequently, AI and DL model-based automated systems have been created to aid in clinical decision-making.

To assess the system's performance, the study [2] used a variety of machine learning classifiers, such as Support Vector Machine, Gradient Boost, K-Nearest Neighbor, XGBoost, and Logistic Regression. The findings demonstrated the accuracy of the various classifiers, with Extreme Gradient Boosting (XGBoost) achieving the highest accuracy of 92.02%. The study aimed to differentiate between benign and malignant brain tumors by using a random forest classifier to extract textural and demographic information from MRI Apparent Diffusion Coefficient images of human brain tumors.

III.PROPOSED WORK

Problem Identification

The class imbalance, insufficient generalization over a variety of datasets, and picture noise are three major challenges that significantly impair the effectiveness of the systems that are now in use [7]. Although some models have added attention methods to increase feature learning and others have employed data augmentation and transfer learning to overcome restrictions in the dataset, these models still have a long way to go before they can be regarded reliable and accurate in applications that are used in the real world. Because there is a scarcity of labelled data, it is already difficult to train models that are accurate and resilient [9].

Kaggle Dataset

Kaggle for brain tumor classification, most of which use MRI scans. Some popular ones include the multimodal Brain Tumor dataset, which allows for thorough analysis, and specialized datasets like Brain Tumor Segmentation Challenge for advanced classification tasks. All of these datasets support deep learning models, such as CNNs, which can be used for automated diagnosis. A total of 3264 T1-weighted, contrast-enhanced MRI images comprised the data that utilized image-based dataset .There were 500 images of a healthy brain in this collection, 937 images of meningiomas, 901 images of pituitary tumors, and 926 images of gliomas. These dataset are publicly available and taken from kaggle. These dataset were verified and validated for the detection of MRI based brain tumor using CNN.

Image Data Loading

For the purpose of loading and pre-processing images in preparation for the subsequent training of the model, this method makes use of the OpenCV library, which is commonly referred to as cv2. It employs the cv2 for each and every image that it discovered in the directory. It does this for every single image.imread() is a function that is utilized to load the picture in grayscale mode, which utilizes 0 pixels as the resolution. Using the cv2.resize() method, the image is scaled to a standard dimension of 200 pixels by 200 pixels after it has been loaded into memory. As a result of these pre-processing procedures, the image data is guaranteed to be uniform and consistent, which makes it simpler to incorporate the data into the machine learning pipeline without causing any disturbances. Following that, the photographs that have been downsized are affixed to a feature array (X), and the suitable class labels are added to a target array (Y). Both of these updates are carried out synchronously with one another. When it comes to this particular instance, every element is a NumPy array that employs a representation of an image that is two-dimensional.

Data Augmentation

Brain tumor classification relies heavily on data augmentation, which involves artificially expanding small MRI datasets using transformations like flips, rotations, shifts, and zooms, as well as advanced techniques like GANs and Mixup. Data augmentation is the process of creating a diverse and artificially large collection of training images. The model's generality has been enhanced by its ability to accommodate variations in tumor size, location, form, and MRI scan parameters. The classification of brain tumors using magnetic resonance imaging images is frequently plagued by issues with dataset size, class imbalance, and scanner parameters. In order to circumvent these challenges, data augmentation is implemented to artificially augment the quantity and diversity of training data. This reduces the probability of over fitting and improves the model's generalizability.

Median Filter

When applied to MRI scans of the brain, this nonlinear technique effectively eliminates unwanted background noise. Edge preservation with this approach is common practise. Salt and pepper noise may be eliminated with great success. Median filter is similar to mean filter in that it iteratively processes an image, but it replaces each pixel's value with the middle value of its neighbours rather than the mean. After sorting all the neighbouring pixel values into numerical order, the median pixel value from the neighbouring pixel values is used to replace the pixel under consideration. When it comes to decreasing noise without diminishing image quality, the median filter is much superior.

HOG feature extraction

The Histogram of Oriented Gradients can identify the local structure and shape of an image. It functions by measuring the gradient orientation distribution in specific areas of the picture. HOG feature extraction entails several key steps: first, the computation of image gradients to capture edge and texture information; then, the division of the image into small, overlapping cells, followed by the quantization of gradient orientations into predefined bins within each cell. Subsequently, histograms of gradient orientations are constructed for each cell, and normalization techniques are applied to enhance the descriptor's robustness to illumination and contrast variations.

ADF Filtering

ADF filtering works based on the concept of Anisotropic Diffusion, where the smoothing process occurs differently in different directions. Unlike normal filters that blur the entire image, ADF selectively smooths homogeneous regions while preserving edges and boundaries of structures. This is very important in medical images because edges often represent important anatomical structures or tumor boundaries. In brain tumor detection, ADF filtering helps by removing noise from MRI images, enhancing the clarity of the brain tissues, and making it easier for algorithms or doctors to identify abnormal regions. The diffusion process is controlled by parameters that determine how much smoothing occurs, ensuring that noise is reduced without losing critical diagnostic information.

Q-BBA

Quantum Binary Bat method is echolocation is a critical characteristic; Yang proposed a bat algorithm that emulates the foraging behavior of bats. Additionally, quantum-enabled algorithms, which encompass both quantum and quantum-inspired algorithms. Finally, the histogram values from all cells are concatenated to form the HOG feature descriptor for the entire image. The Quantum Binary Bat Algorithm is a powerful optimization technique for brain tumor detection, especially in feature selection. By combining bio-inspired and quantum principles, QBBA enhances the efficiency and accuracy of detection systems. It is particularly useful in medical image analysis where handling large and complex datasets is critical. The Quantum Binary Bat Algorithm is an advanced optimization technique used in brain tumor detection to improve the accuracy and efficiency of classification systems. It is derived from the Bat Algorithm, which is inspired by the echolocation behavior of bats, and is enhanced with quantum principles to provide better search capabilities.

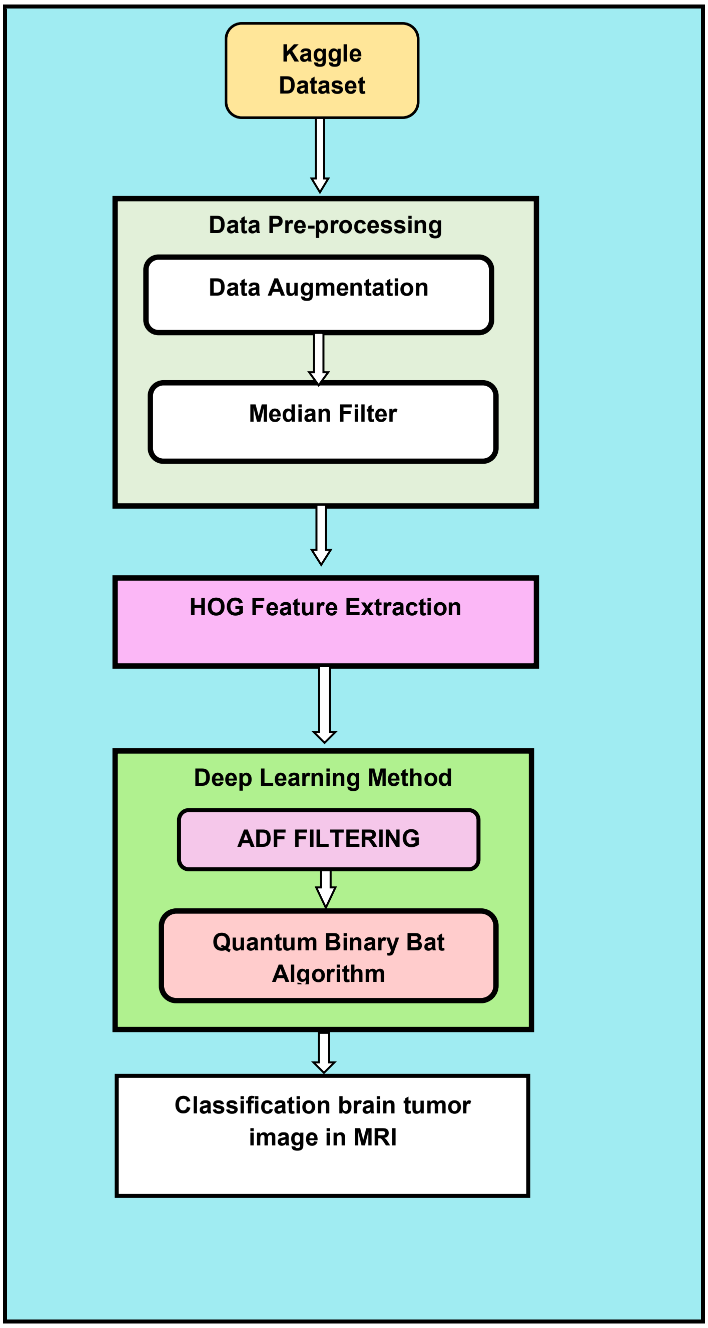


Fig. 3.1 Flow Diagram of Q-BBA method

The selected optimal feature subset is then used by classifiers such as Support Vector Machines or Convolutional Neural Networks to accurately distinguish between tumor and non-tumor regions. As a result, QBBA significantly improves detection performance, reduces computational complexity, and enhances the overall reliability of brain tumor diagnosis systems. C is the symbol for the ideal feature in hybrid optimization, while $\emptyset$ is used to represent the mapping of features. Methods for incorporating Efficient Q-BBA.

QBBA is primarily used for feature selection, where it identifies the most relevant features from MRI images while eliminating redundant and irrelevant data. The algorithm represents solutions in binary form, where each bit indicates whether a feature is selected or not. By applying quantum-based probabilistic updates, QBBA efficiently explores the search space and avoids local optima. The selected optimal feature subset is then used by classifiers such as Support Vector Machines or Convolutional Neural Networks to accurately distinguish between tumor and non-tumor regions. As a result, QBBA significantly improves detection performance, reduces computational complexity, and enhances the overall reliability of brain tumor diagnosis systems.

Proposed Q-BBA Algorithm for Brain Image Classification in MRI

Step 1:	Input Kaggle dataset Height× Width × Channels. Bilateral or Median filters Save feature maps *Fi* selected layers for skip connections.
Step 2:	Initialize quantum-inspired population QP of size N Each individual represents a binary feature selection mask Apply quantum rotation gates to explore solution space
Step 3:	Update QP using quantum-inspired operators: Apply quantum Hadamard transformation Apply adaptive rotation gate based on global best and current best

Step 4:	Extract best feature subset F_opt from best individual
Step 5:	Apply serial fusion: F_fused = concatenateb(F_opt from F1 and F2)
Step 6:	Genetic Algorithm of minimal radiation brain tumor identification exposure.
Step 7:	Classify fused using NN classifier
Step 8:	Brain tumor Image classification using Q-BBA
Step 9:	Evaluate new opinion and renew the best solution X^*
Step 10:	Position and velocity of each sperm using the quantum based binary bat algorithm
Step 11:	If exploration is chosen (based on parameter a),
Step 12:	End

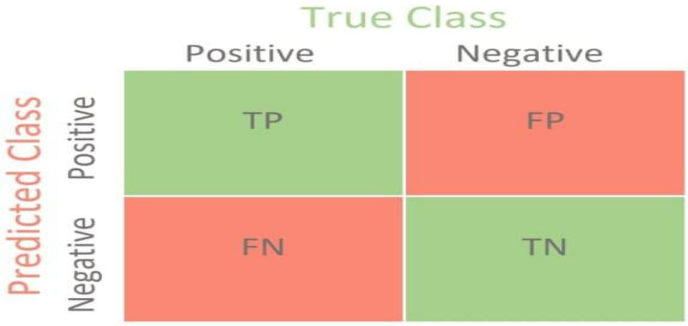
This contributes to the resolution of the prevalent issue of expensive and scarce medical data by enhancing the robustness of deep learning models, reducing the probability of overfitting, and enhancing the precision of tumor detection and segmentation. The use of limited and uneven MRI datasets for brain tumor classification can result in overfitting in deep learning models.

IV. RESULTS AND DISCUSSION

The Q-BBA method is exceptionally resilient in situations involving anatomical structures with irregular shapes or minuscule lesions due to its ability to efficiently acquire and integrate hierarchical data. Furthermore, the symmetrical architecture of the encoder and decoder paths enables effective learning and optimization, while the skip connections mitigate the risk of data loss during feature down sampling.

Precision

Precision metrics are measurements used to evaluate how accurate or consistent a system's predictions or results are, especially in fields like data science, machine learning, and information retrieval.



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.

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.

$$\boldsymbol{Recall = \frac{TP}{TP+FN}} \qquad \text{---------(4.1)}$$

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 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.

$$\boldsymbol{F1 - Score = \frac{2X(\,Precision\ X\ Recall)}{Precision + Recall}} \qquad \text{----(4.2)}$$

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.

$$Accuracy = \frac{TP+TN}{FP+FN} \quad \text{----- (4.3)}$$

From fig 4.1 displays 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.

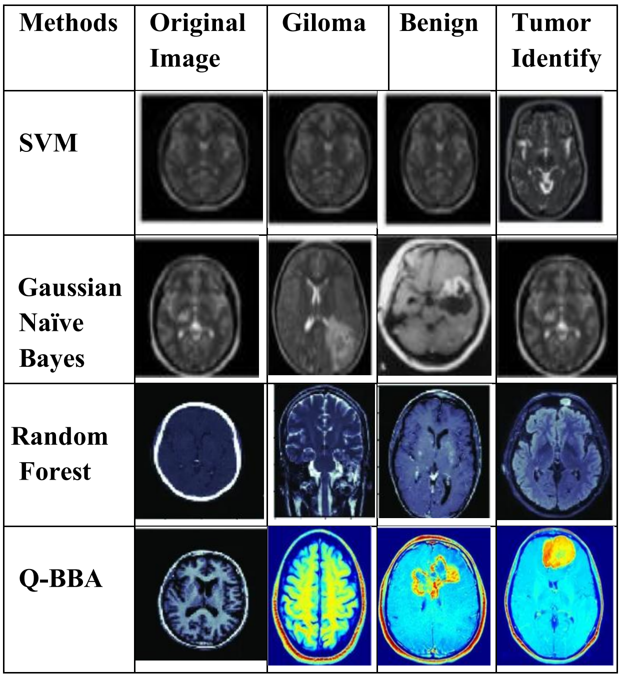


Fig.4.1 Comparative Analysis of Brain Tumor Classification Methods

Common tumor types include glioma, meningioma, and pituitary tumors, each having distinct characteristics growth patterns. The Giloma, Bengin, Meningioma and tumor identifications. Brain tumor pathological diagnosis is the process of identifying and confirming a brain tumor by examining tumor tissue under a microscope. After imaging tests such as MRI or CT scans suggest the presence of a tumor, doctors perform a biopsy or surgical removal of tumor tissue. The collected tissue sample is then analyzed by a pathologist in a laboratory to determine the type, grade, and characteristics of the tumor cells. In binary brain tumor detection, the system first preprocesses MRI images and converts the features into a quantum representation.

This diagnosis is considered the most accurate method for confirming brain tumors. The results help doctors decide the most appropriate treatment plan, which may include surgery, radiation therapy, or chemotherapy. Brain tumor detection using MRI images requires accurate feature selection and classification to distinguish between normal and abnormal tissues. Optimization algorithms are often used to improve model performance. One such advanced method is the Quantum Binary Bat Algorithm (QBBA), which combines the principles of the Bat Algorithm with quantum computing concepts to enhance search efficiency and accuracy in binary problem spaces.

Table 4.1 Comparative table of tumor methods Classification

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
Q-BBA	95.1	95.2	95.4	96.8

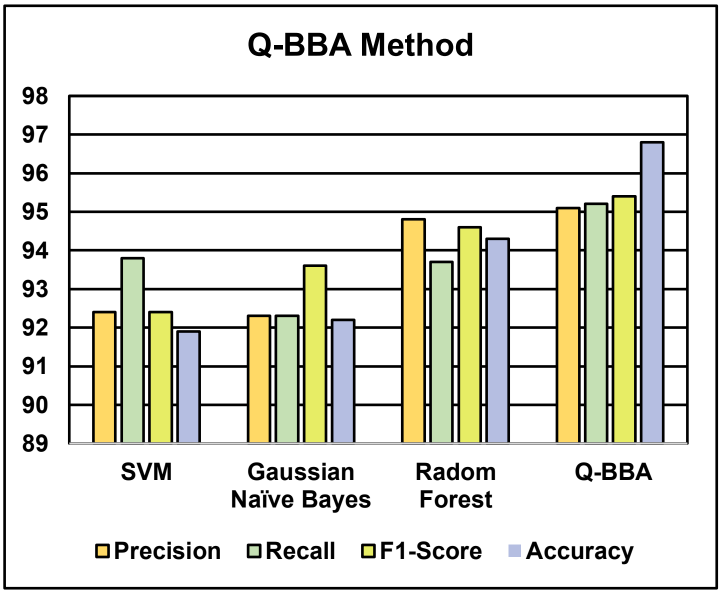


Fig.4.2 Comparative chart of tumor methods Classification

From fig.4.2 this work enhances brain tumor detection by employing hybrid feature selection algorithms that integrate firefly and glow worm optimization techniques, utilizing the Q-BBA algorithm.

V. CONCLUSION

The proposed work Quantum-Binary Bat method is primarily contributes to brain tumor detection by using hybrid feature selection algorithms that combine firefly and glow-worm optimization algorithms for feature selection. It also employs the Q-BBA algorithm and stacking ensemble classifier for classification. Additionally, it applies the feature of fusion of different feature extraction methods. MRI texture features are extracted using the Q-BBA approach. The correct location of brain cancer is the intended result of the proposed stacking outfit calculation for brain tumor identification.

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