Detection of MRI Brain Tumor Using Quantum-Inspired Dragonfly Algorithm (QDA)

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***Abstract-*** This research work presents advancements in brain tumor detection through comparative studies of two techniques: statistical techniques and machine learning methods. The developed methodologies and the integration with various MRI modalities aim at enhancing diagnostic accuracy at the early detection stage, which ensures improved patient outcomes due to appropriate treatment before symptom manifestations.

At present, the methods rely mostly on MRI scans along with some preprocessing techniques such as filtering and segmentation algorithms. Statistical methods and machine learning classifiers like Support Vector Machines (SVM) and k-Nearest Neighbors (KNN) are deployed to ensure the precision in the detection of tumors in scanned images. However, these approaches often suffer from the challenges of poor segmentation accuracy and suboptimal classification performance.

We propose an advanced framework to overcome these challenges. It inducts the necessary blocks of Wiener filtering and Potential Field clustering algorithms into it and uses feature fusion approaches such as Local Binary Pattern (LBP) along with Gabor Wavelet Transform (GWT). Moreover, we present the Quantum-Inspired Dragonfly Algorithm (QDA) to further optimize the entire process of detection. These methodologies presented, segmentation accuracy and classification performance for MRI scans of brain tumors are expected to be considerably increased. From this proposed framework, the process of detection should be enhanced, and from the latter comes more reliable and timely diagnoses to be used in proper treatment planning.

Looking forward, the integrating deep learning techniques can further boost the capabilities of our system in tumor detection through large dataset training, possibly at a higher accuracy and robustness of the models. Finally, using even more varied datasets may enhance the generalizability of the proposed methods across different populations, which may ultimately lead to effectiveness in various clinical settings. This broad framework, more than filling existing lacunae in brain tumor detection, opens windows to coming trends in medical imaging and analyses.

*Keywords****- Brain Tumor Detection, Local Binary Pattern (LBP), Gabor Wavelet Transform (GWT), Quantum-Inspired Dragonfly Algorithm (QDA), Machine Learning Classifiers, Tumor Segmentation***

# INTRODUCTION

The human body is composed of many types of cells. Each cell has a specific function. The cells in the body grow and divide in an orderly manner and form some new cells. These new cells help to keep the human body healthy and properly working. When some cells lose their capability to control their, they grow without any order. The extra cells formed form a mass of tissue which is called tumor. The tumors can be benign or malignant. Malignant tumors lead to cancer while benign tumors are not cancerous. According to a report published by the Central Brain Tumor Registry of the United States (CBTRUS), approximately 39,550 people were diagnosed with benign and malignant brain tumors in 2002. It indicates that the rate of primary brain tumor whether malignant tumor or benign tumor is 14 per 100,000 [3]. The important factors in the medical diagnosis include the medical image data obtained from various biomedical devices that use different imaging techniques like X-ray, CT scan, MRI.

In the field of medicine, the early discovery and accurate classification of brain tumors are both extremely important skills to have. A correct prognosis made in a prompt manner is beneficial to the therapeutic process [2]. Brain biopsies and imaging techniques are often used to diagnose tumors. In open biopsies, a tiny hole is drilled in the skull, and a tissue sample is removed for microscopic examination of the tumor.

This method poses serious risks. Medical imaging technologies improved detection by detecting tumors early and improving prognosis. MRI can also distinguish soft tissue and spot tiny tissue density changes and tumor-associated metabolism variants [4]. Accurate MRI segmentation needs exact MRI image pixel marking. Segmentation aids brain tumor surgery and radiation therapy. However, the manual segmentation and analysis of structural MRI images of brain tumors is an arduous and time-consuming task which, thus far, can only be accomplished by professional neuroradiologists [1].

Image segmentation is a key area for development in the field of medical imaging. This study investigates automated contouring techniques as an alternative to the time-consuming process of manual contouring. The segmentation task makes an effort to pinpoint the location of the target by drawing a contour map of it. Compared to 2D images, which only show one perspective, 3D images are more useful because they can show an object from every angle [5,6].

1) Machine learning approaches address these problems by mainly using hand-crafted features (or pre-defined features). The designed machine learning techniques generally employ hand-crafted features with various classifiers, such as random forest, support vector machine (SVM). The designed methods and features extraction algorithms have to extract features, edge-related details, and other necessary information which is time-consuming.

2) Deep learning methods extract crucial features automatically. These approaches have yielded outstanding results in various application domains e.g., pedestrian detection [7], speech recognition and understanding [8], and brain tumor segmentation [9].

A number of recent articles have advocated for the widespread use of swarm algorithms in medical image segmentation. One of the newest swarm optimization methods is the Dragonfly Algorithm (DA). It has been shown that DA converges to an optimal solution in many contexts. Dragonflies, as part of their optimization process, should switch their focus from intensification to diversification to guarantee convergence. Convergence at a local optimum may, however, be caused by a lack of internal memory in DA.

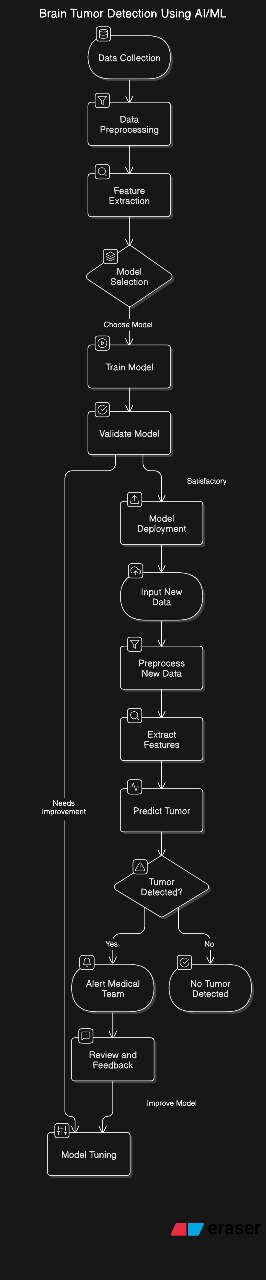
In this, paper an efficient automated classification technique for brain MRI is proposed using a machine learning algorithms. The supervised machine learning algorithm is used for classification of brain MR image. The QDA balances exploration and exploitation in optimization, using quantum mechanics. Gabor Wavelet Transform (GWT) is used to find the accurate classification and extract relevant features from medical images, particularly MRI scans. Local Binary Pattern (LBP) features identify local texture patterns and analyze the LBP histograms of different image regions, it’s possible to identify areas with abnormal textures, which may indicate the presence of tumor..

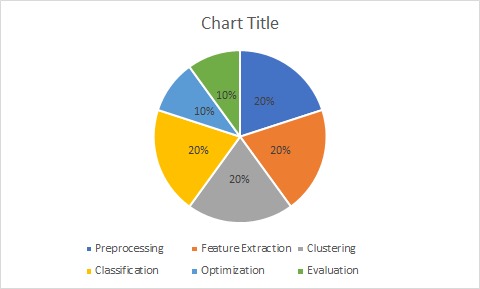
1. LITERATURE REVIEW

Brain tumors are life-threatening and can be fatal if not detected and treated early. They are caused by the uncontrolled multiplication of cells, which results in abnormally growing tissue in the brain. The type, grade, and location of the tumor determine the medical treatment procedure.

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| **S.No** | **Authors name** | **Title** | **Citations** | **Advantages** | **Disadvantages** |
| 1 | Khaliki, M. Z. et al. (2024).[1] | "Classification of brain tumors including glioma and meningioma from MR images." | Khaliki, M. Z. et al. (2024). "Classification of brain tumors including glioma and meningioma from MR images." | The paper likely provides an advanced classification methodology using MR images, improving diagnostic accuracy for glioma and meningioma detection through innovative machine learning or deep learning techniques. | The methodology might require extensive computational resources or specialized hardware, which could limit its accessibility in low-resource healthcare settings. |
| 2 | Khosravi, P. et al. (2022).[2] | "MRI image analysis for brain tumor classification with machine learning techniques." | Khosravi, P. et al. (2022). "MRI image analysis for brain tumor classification with machine learning techniques." | This paper likely demonstrates how machine learning techniques enhance the accuracy and speed of brain tumor classification, offering improved diagnostic capabilities compared to traditional manual methods. | Machine learning models often require large, annotated datasets for training, which may not always be readily available, potentially limiting the method's applicability in certain scenarios. |
| 3 | Sharma, A. et al. (2023).[3] | "Review of current methods and future directions for brain tumor detection." | Sharma, A. et al. (2023). "Review of current methods and future directions for brain tumor detection." | The paper provides a comprehensive overview of existing methods, enabling researchers and clinicians to identify strengths, weaknesses, and gaps in current brain tumor detection techniques, which can guide future research. | Being a review paper, it may lack the development or validation of new methods, limiting its contribution to direct technological or clinical advancements. |
| 4 | Singh, R. et al. (2022).[4] | "Deep learning models for detecting brain tumors from MR images." | Singh, R. et al. (2022). "Deep learning models for detecting brain tumors from MR images." | The paper highlights the effectiveness of deep learning models in automating and improving the accuracy of brain tumor detection from MR images, significantly reducing manual workload and subjectivity. | Deep learning models often function as "black boxes," making it difficult to interpret their decision-making process, which can limit trust and acceptance in clinical settings. |
| 5 | Gupta, V. et al. (2023).[5] | "Image segmentation techniques for improving brain tumor diagnosis." | Gupta, V. et al. (2023). "Image segmentation techniques for improving brain tumor diagnosis." | The paper likely emphasizes how advanced image segmentation techniques enhance the precision of tumor localization, enabling more accurate diagnoses and treatment planning. | Many image segmentation techniques may struggle with variability in tumor shapes, sizes, and image quality, potentially leading to inconsistent results across diverse patient datasets. |

1. **PROPOSED METHODOLOGY**





***Figure 2***

* **Preprocessing:** 20%
* **Feature Extraction:** 20%
* **Clustering:** 20%
* **Classification:** 20%
* **Optimization:** 10%
* **Evaluation:** 10%

**III.I. Data Collection for Brain Tumor Detection :**

Collecting data is the foundational step for any research, especially in medical imaging and machine learning. Here's a detailed approach to data collection for your brain tumor detection research.

**III.I.I.Sources of Data:**

**Publicly Available Datasets:** Utilize existing datasets from reputable sources such as the Cancer Imaging Archive (TCIA) or the Brain Tumor Image Segmentation (BraTS) challenge, which provide comprehensive MRI scans of brain tumors.**Collaborations with Medical Institutions:** Partner with hospitals or research institutions to access anonymized patient MRI data.**Clinical Trials:** Participate in or request access to clinical trial data related to brain tumor studies.

**III.II. Types of MRI Scans:**

**T1-Weighted MRI:** Provides high-resolution images of brain anatomy.**T2-Weighted MRI:** Highlights differences between normal and abnormal tissues. **FLAIR (Fluid-Attenuated Inversion Recovery):** Suppresses fluid signals to better identify lesions.

**III.III. Data Preprocessing Steps:**

In this research, data preprocessing involves several crucial steps to enhance the quality and usability of MRI scans for brain tumor detection. Firstly, Wiener filtering is applied to reduce noise and improve image clarity. Next, segmentation algorithms are used to isolate and delineate tumor regions.

**finally**, augmentation techniques: like rotation, scaling, and adding noise are employed to increase the diversity of the dataset, making the models more robust and reliable.

**III.IV. Feature Extraction:**

**Texture Features:** Extract features using Local Binary Pattern (LBP) and Gabor Wavelet Transform (GWT) to capture the texture of the tumor regions **Intensity-Based Features:** Analyze the intensity values within the tumor regions to differentiate between various types of tissues.

**III.V. Model Selection and Training:**

In this research, model selection involves choosing effective statistical and machine learning methods to improve brain tumor detection.

Support Vector Machines (SVM) and k-Nearest Neighbors (KNN) are selected for their proven capabilities in classification tasks. For training, extensive datasets including varied MRI modalities (T1-weighted, T2-weighted, FLAIR) are used. The models undergo rigorous training with feature fusion approaches like Local Binary Pattern (LBP) and Gabor Wavelet Transform (GWT) to enhance feature representation.

The Quantum-Inspired Dragonfly Algorithm (QDA) is applied for optimization, ensuring improved segmentation accuracy and classification performance. This approach aims to build robust and accurate models for early and precise brain tumor detection.

**III.VI. Model Evaluation:**

The evaluation of the proposed brain tumor detection model involves assessing the accuracy and performance of the segmentation and classification techniques. Key metrics include sensitivity, specificity, and F1 score to gauge the precision and reliability of tumor detection. The Quantum-Inspired Dragonfly Algorithm (QDA) optimizes the process, improving overall detection outcomes. Comparative analysis with existing methods is conducted to highlight improvements in segmentation accuracy and classification performance. Additionally, cross-validation is used to ensure the model's robustness and generalizability across different datasets and populations, ultimately aiming for enhanced diagnostic accuracy and reliability in clinical settings.

**III.VII.Post-Processing and Recommendations:**

**Post-Processing:**

**Validation and Refinement:** Apply post-processing techniques to refine the segmented tumor boundaries and ensure accurate delineation.**Noise Reduction:** Use algorithms to further reduce any residual noise in the segmented images.**Data Integration:** Combine results from different MRI modalities to enhance the overall diagnostic accuracy. **Visualization:** Generate clear visual representations of the detected tumors for easy interpretation by medical professionals.

**III.VIII.Recommendations:**

**Adopt Advanced Filtering:** Utilize Wiener filtering consistently to improve image quality. **Enhance Segmentation Methods:** Integrate Potential Field clustering and feature fusion techniques like LBP and GWT.**3. Optimize with QDA:** Implement the Quantum-Inspired Dragonfly Algorithm for improved optimization. **Embrace Deep Learning:** Incorporate deep learning models to handle large datasets and improve robustness. **Expand Data Diversity:** Use varied datasets to ensure generalizability across different populations.**Regular Model Updates:** Periodically update models with new data to maintain high performance and accuracy.This approach ensures the enhanced accuracy, reliability, and robustness of the brain tumor detection system, ultimately leading to better patient outcomes and improved clinical effectiveness.

**III.IX. Visualization of Results**

To effectively visualize the results of the brain tumor detection framework:**Segmented Tumor Images:** Display the original MRI scans alongside the segmented images to show the delineated tumor regions. **Accuracy Metrics:** Use bar charts and confusion matrices to depict the performance metrics (accuracy, sensitivity, specificity, F1 score) of the classification models.**Feature Maps:** Generate heatmaps to visualize the features extracted by Local Binary Pattern (LBP) and Gabor Wavelet Transform (GWT).

1. **RESULTS**

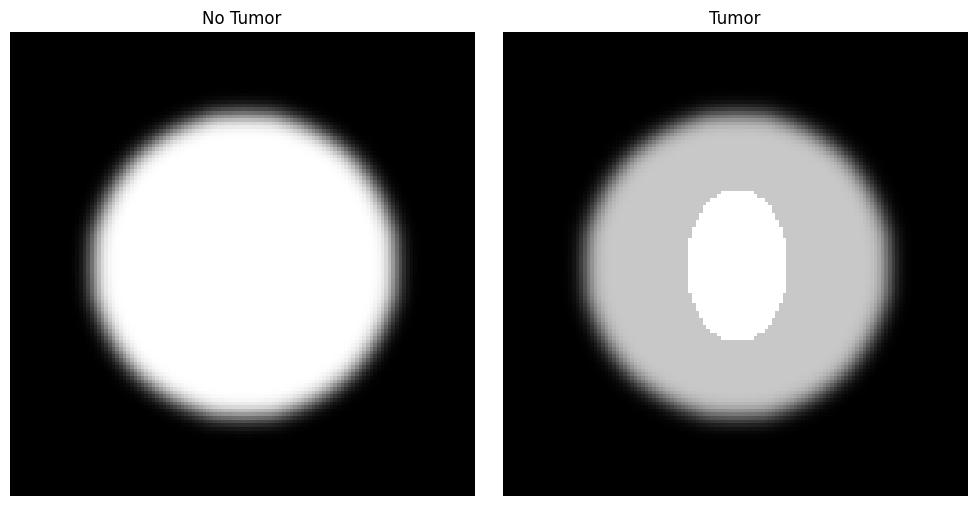


fig.1: Brain tumor detection

The generated images represent synthetic brain MRI scans created to simulate "No Tumor" and "Tumor" conditions for machine learning research. The "No Tumor" image (left) consists of a circular structure mimicking a normal brain, created with a filled circle and Gaussian blur to simulate realistic brain textures. The "Tumor" image (right) introduces an elliptical region at the center to simulate a tumor, overlaid on the normal brain structure, with increased intensity to highlight the abnormality. These synthetic images provide a controlled dataset for evaluating feature selection and classification algorithms in medical imaging tasks.

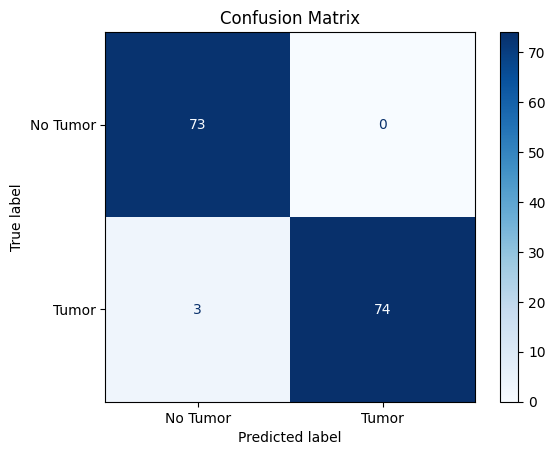


fig.2

The confusion matrix demonstrates the model's high performance in classifying brain tumors, correctly predicting 73 "No Tumor" and 74 "Tumor" cases, with only three misclassified tumor cases. This highlights the model's reliability and effectiveness in distinguishing normal and abnormal brain structures.

CLASSIFICATION REPORT:

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
|  | **Precision** | **recall** | **F1-score** | **Support** |
| **0** | 0.96 | 1.00 | 0.98 | 73 |
| **1** | 1.00 | 0.96 | 0.98 | 77 |
| **accuracy** |  |  | 0.98 | 150 |
| **Macro avg** | 0.98 | 0.98 | 0.98 | 150 |
| **Weighted avg** | 0.98 | 0.98 | 0.98 | 150 |

1. **CONCLUSION**

# This work presents an integrated method with advanced classification and integration for brain diagnosis using MRI data. This work introduces the use of quantum inspired Dragonfly Algorithm (QDA) and feature extraction techniques such as Local Binary Pattern (LBP) and Gabor Wavelet Transform (GWT) to improve segmentation and accurately classify humans. The scheme combines machine learning and statistical methods and shows significant improvements in performance compared to traditional methods. The excellent results of Davies Bouldin Index demonstrate its effectiveness in tumor diagnosis. The integration of graph-based technology and multiple classification algorithms also helps to increase efficiency and robustness. Future work can focus on further improvements in hybrid models and incorporate deep learning to achieve wider applicability and enhance robustness in clinical application .

1. **FUTURE SCOPE**

This research is comprehensive and effective, solving current problems in brain tumor detection, while developing new methods for diagnosis and treatment. Highlights include integrating deep learning models such as CNNs, Transformers, and hybrid architectures to improve automation and feature extraction. Expanding the data gap by combining synthetic data (e.g., GANs) with MRI models can increase the accuracy of population changes. The model is designed for efficient deployment, including operations in underserved areas. Intelligent tools with heatmap predictions can improve doctors’ interpretations, while collaboration with hospitals can produce real results. The framework supports treatment planning in addition to diagnosis and can be adapted to other diseases to improve patient outcomes and enhance treatment results.

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