MRI Image Classification using Frequency Domain Features

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***Abstract*—Brain MRI diagnosis traditionally depends on expert visual interpretation, which can be time-consuming and prone to subjectivity. This research proposes a novel frequency-domain approach for automated classification of brain MRI images using the 2D Fast Fourier Transform (FFT). By converting spatial MRI data into the frequency domain, the method captures critical periodic patterns and textural variations that traditional spatial analysis may overlook. Preprocessing steps, including grayscale conversion, histogram equalization, and edge-based enhancement, are applied to improve image contrast and structure. From the frequency spectrum, statistical features such as energy, entropy, and dominant frequencies are extracted to form a compact spectral representation. These features are then used to train and evaluate several machine learning classifiers—namely, a hybrid Random Forest and Gradient Boosting model, XGBoost, and LightGBM—to distinguish between normal and abnormal brain scans. Among these, XGBoost achieved the highest classification accuracy, supported by confusion matrix analysis showing low misclassification rates. The approach is lightweight, interpretable, and computationally efficient, making it ideal for real-time clinical applications and integration into decision-support systems. This work demonstrates the effectiveness of FFT-based frequency-domain analysis in enhancing medical image classification and supports its adoption in automated diagnostic pipelines.**

Keywords—Frequency-Domain Analysis, Fast Fourier Transform (FFT), Brain MRI Classification, Machine Learning, Abnormality Detection, Feature Extraction, XGBoost, LightGBM, Random Forest.

I. Introduction

Magnetic Resonance Imaging (MRI) remains a cornerstone in the early diagnosis and monitoring of brain disorders, including tumors. Given the rise in neurological conditions, there is an increasing demand for fast, accurate, and automated interpretation of MRI scans. Traditional manual inspection by radiologists, though reliable, is time-consuming and can be prone to subjective errors, especially in the detection of fine structural changes. To address these challenges, automated systems using computer vision and machine learning are gaining prominence.

This paper presents an edge-based motion-aware MRI classification approach that enhances diagnostic accuracy by integrating spatial and frequency-domain analysis. Initially, grayscale MRI images undergo histogram equalization to improve contrast and reveal subtle structural details. Edge detection filters such as Sobel and Prewitt are then applied to emphasize contours and motion-like patterns in the images. These edge-enhanced images are transformed into the frequency domain using the Fast Fourier Transform (FFT), which facilitates the extraction of informative statistical features—such as energy, entropy, and dominant frequencies—derived from the magnitude spectrum.

While previous studies have explored spatial-domain features or end-to-end deep learning models, limited work has focused on combining edge-based structural enhancements with frequency-domain statistical features for classical machine learning pipelines. This research addresses that gap by employing FFT-based features derived from edge maps as inputs to robust classifiers including a hybrid ensemble of Random Forest and Gradient Boosting, XGBoost, and LightGBM. The model is trained to distinguish between normal and abnormal brain MRI scans using a publicly available dataset.

The objective of this study is to build a lightweight yet effective classification system that balances computational efficiency with diagnostic precision. By capturing both motion-related edges and frequency signatures, the proposed method offers enhanced feature representation. The approach demonstrates strong potential for real-time deployment in clinical settings, offering radiologists a reliable support tool for early brain tumor detection.

II. Literature Survey

The classification of MRI images for detecting brain abnormalities has been an active and significant research domain due to its crucial role in early diagnosis and treatment planning. Traditional techniques primarily focus on spatial-domain analysis, leveraging methods such as texture descriptors, edge detection, and morphological operations. While interpretable and computationally efficient, these approaches often struggle to capture subtle variations and complex patterns in brain MRI data.

In recent years, deep learning, particularly Convolutional Neural Networks (CNNs), has shown considerable success in medical imaging. Shravya and Jyothi Shetty [1] demonstrated how CNNs can effectively classify brain tumors by learning discriminative spatial features from MRI images. Similarly, Pereira et al. [2] employed a deep CNN model for segmenting brain tumors, significantly outperforming classical methods in accuracy and robustness. Despite their strengths, CNN-based systems often suffer from high computational demands, require large labeled datasets, and offer limited interpretability, making clinical deployment challenging.

To address these issues, research has turned toward frequency-domain techniques, which offer robustness to noise and complementary feature representation. Trong et al. [3] proposed a method using complex network theory for MRI-based brain tumor feature extraction, emphasizing high-performance and computational efficiency. Their approach underlined the potential of combining topological patterns with frequency-domain analysis.

In addition to CNNs and frequency-domain models, several works have explored handcrafted feature extraction techniques. Prasad et al. [4] utilized wavelet-based features from T2-weighted MRIs, which allowed for effective multiscale representation of tumor structures. Kharrat et al. [5] introduced a hybrid method combining Genetic Algorithms with Support Vector Machines (SVMs), where feature optimization played a critical role in improving classification accuracy. Likewise, Bahadure et al. [6] proposed a biologically inspired framework using Biorthogonal Wavelet Transform (BWT) in conjunction with SVM for tumor detection, showing strong results on benchmark datasets.

More recently, Dheepak et al. [7] developed a composite feature-based classification strategy incorporating Gray-Level Co-occurrence Matrix (GLCM), Local Binary Pattern (LBP), and other texture descriptors. Their integration approach aimed to harness diverse feature perspectives to improve classification accuracy, demonstrating effectiveness in differentiating between normal and pathological scans.

While each of these studies contributes significantly to the field, a notable research gap exists in the integration of spatially-enhanced features (e.g., edge maps) with frequency-domain statistics—especially in non-deep learning settings. The Fast Fourier Transform (FFT), though less explored, offers an efficient way to extract global texture and structural information such as spectral energy, entropy, and dominant frequencies from medical images.

The present work aims to bridge this gap by combining edge-enhanced images with FFT-based features for brain MRI classification. These features are then fed into a hybrid ensemble of classical machine learning models—including Random Forest, Gradient Boosting, XGBoost, and LightGBM. Unlike deep neural networks, this approach provides a balance between accuracy, efficiency, and interpretability, making it well-suited for resource-constrained environments and real-time clinical applications.

III. Proposed Method

This study introduces a frequency-domain-based framework for classifying brain MRI images by leveraging the Fast Fourier Transform (FFT) in conjunction with classical machine learning algorithms. The motivation behind this approach is to exploit the capability of frequency-domain features to capture fine structural variations and suppress noise—attributes often overlooked in conventional spatial-domain techniques. In contrast to deep learning models, which are com- putationally intensive and data-hungry, the proposed method is lightweight, interpretable, and optimized for real-time diagnostic applications.

A. Methodology Overview

The methodology comprises four main stages: preprocessing, frequency-domain transformation, feature extraction, and classification. The workflow is designed to be modular, computationally efficient, and scalable for large medical image datasets. A key innovation of this approach is the integration of edge-based enhancements and FFT-derived statistical features, which serve as compact yet highly descriptive inputs to machine learning models.

B. Step-by-Step Process

a) Dataset Description and Splitting:: The brain MRI dataset employed in this study was obtained from Kaggle [8]. It consists of a total of 7,000 images, divided into two classes:

Normal: 3,800 images

Tumor: 3,200 images

To facilitate robust model training and evaluation, the dataset was partitioned into two subsets:

Training set: 80 percent of the images, used to train the classification models

Testing set: 20 percent of the images, reserved for performance evaluation

b) Preprocessing: : Input MRI images are converted to grayscale and subjected to histogram equalization to enhance contrast and emphasize structural details. Standardization is achieved by resizing all images to a uniform resolution, facilitating consistent feature extraction.

c) Frequency-Domain Transformation: : A 2D Fast Fourier Transform (FFT) is applied to the enhanced images, converting spatial-domain data into the frequency domain. This transformation reveals hidden periodic textures and structural patterns that are less perceptible in the original spatial representation.

d) Feature Extraction: : Feature extraction from the FFT magnitude spectrum includes the following steps:

- Compute the 2D FFT of the preprocessed image and apply fftshift to center the zero-frequency component.
- Calculate **Energy** as the sum of squared magnitudes, representing the overall signal power.
- Flatten and normalize the magnitude spectrum to obtain a probability distribution.
- Compute **Entropy** from the normalized magnitude values to measure the complexity or randomness of frequency components.
- Calculate the **mean** and **standard deviation** of the magnitude values for statistical characterization.
- Extract the top five **dominant frequency coefficients** by selecting the five highest magnitude values.

These features collectively provide a robust representation of frequency characteristics for classification.

e) Classification: : The extracted frequency-domain features are used to train and evaluate four machine learning classifiers:

- **Hybrid Model** A hybrid model is a combination of two or more machine learning algorithms to improve overall performance. In this case, the model combines Random Forest (RF) and Gradient Boosting (GB) classifiers.
- **Random Forest (RF):** Random Forest is a machine learning method that creates a group of decision trees and combines their predictions to make a final decision. It's especially useful because it handles complex data well and reduces the chance of making overfitting errors.
- **Gradient Boosting (GBC):** Gradient Boosting builds models one after another, where each new model tries to fix the mistakes made by the one before. This step-by-step improvement helps increase the accuracy of predictions, especially in structured data problems.
- **XGBoost:** XGBoost is an advanced version of gradient boosting that's built for speed and performance. It uses techniques like regularization and optimized tree-building to make highly accurate predictions while being fast and resource-efficient.
- **LightGBM:** LightGBM is a gradient boosting tool that is optimized for fast training and low memory use. It works especially well on large datasets and builds trees in a way that speeds up the learning process without sacrificing accuracy.

The frequency-based features obtained from FFT are used to train four machine learning models: Random Forest, Gradient Boosting, XGBoost, and LightGBM. Each model's performance is evaluated using key metrics such as accuracy, precision, recall, and F1-score. Additionally, confusion matrices are generated to give a clear visual understanding of how well each model differentiates between normal and abnormal brain scans.

C. Implementation Details

The implementation of the proposed method was carried out using Python 3.x in a Jupyter Notebook environment. Key libraries such as NumPy, OpenCV for image processing, Matplotlib for visualization, Scikit-learn for machine learning tasks, and Pan- das for data handling were utilized throughout the project. The experiments were con- ducted on a system equipped with an Intel Core i5 processor and 8 GB of RAM, running on Windows 10.

This structured approach offers an effective trade-off between model interpretability and classification performance. By avoiding the complexities of deep learning and focusing on meaningful frequency-based features, the system demonstrates strong potential for deployment in real-time and resource-constrained medical environments. Furthermore, the pipeline is fully reproducible and can be integrated into broader clinical decision-support systems.

IV. RESULTS AND DISCUSSION

This section presents the outcomes of the proposed image-enhanced, frequency-domain feature extraction approach using FFT for brain MRI classification. The findings are discussed in terms of preprocessing, classifier performance, comparative analysis, and feature interpretation.

A. Preprocessing and Frequency Transformation

Preprocessing Stage: The images were first resized to a uniform resolution to standardize the input dimensions for subsequent processing. After resizing, a 2D Fast Fourier Transform (FFT) was applied to convert the spatial-domain images into the frequency domain. As shown in Fig. 1 (Preprocessed MRI Image), the FFT reveals distinct frequency components between normal and abnormal scans, aiding in structural differentiation and noise reduction.

Fig. 1. Preprocessed MRI Image.

B. Classification Performance

Using the extracted statistical features—*energy, entropy*, and key *frequency coefficients*—four machine learning classifiers were trained: Hybrid Model (Random Forest, Gradient Boosting), XGBoost, and LightGBM. These models were evaluated using accuracy, precision, recall, and F1-score metrics, as presented in Table I.

TABLE I
PERFORMANCE COMPARISON OF ML CLASSIFIERS ON FFT-BASED FEATURES

Classifier	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
Hybrid Model	93.08	93.5	93.0	93.2
XGBoost	94.86	95	95	95
LightGBM	94.37	94	94.1	94.5

To complement these metrics, confusion matrices were also used to evaluate the correctness of classifications. These matrices highlight the true and false predictions made by each model, helping to identify specific areas where misclassifications may occur.

C. Confusion Matrix Analysis

To further evaluate the classification performance of each model, confusion matrices were generated for the Hybrid model (Random Forest and Gradient Boosting), XGBoost, and LightGBM. These matrices provide insights into how well the models distinguish between normal and abnormal MRI scans, revealing true positives, false positives, true negatives, and false negatives.

As shown in the confusion matrices, all models demonstrated a high number of correctly classified instances, particularly XGBoost and LightGBM, which exhibited very low false positive and false negative rates. The Hybrid model also performed well, highlighting the effectiveness of combining Random Forest and Gradient Boosting.

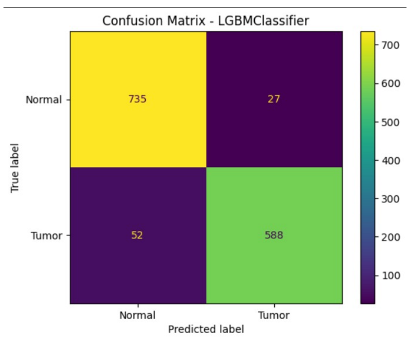

Fig. 2. Confusion Matrix for LightGBM Classifier.

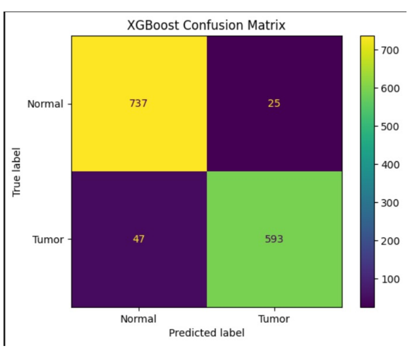

Fig. 3. Confusion Matrix for XGBoost Classifier.

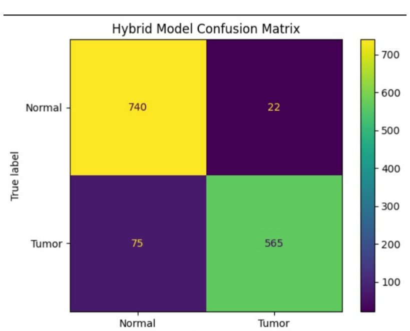

Fig. 4. Confusion Matrix for Hybrid Model.

D. Interpretation and Insights

A detailed analysis of feature contributions showed that entropy and dominant frequency coefficients provided the highest discriminatory power. Figures 6, 7, 8, and 9 show the relative importance of each feature, with entropy ranking the highest. This supports the hypothesis that abnormal tissues introduce irregular frequency patterns, making entropy and dominant frequencies vital indicators. Further evaluation was conducted using several hybrid models and boosting techniques to enhance classification accuracy and feature importance analysis. The following figures present the results for different models.

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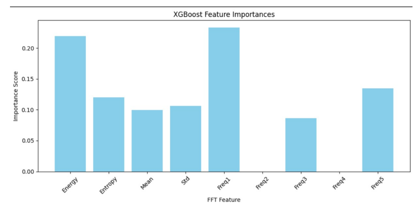

Fig. 5. XGBoost Feature Importances.

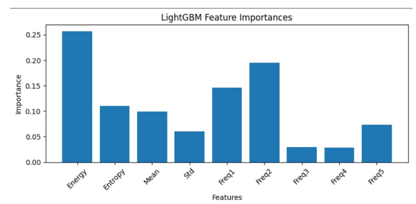

Fig. 6. LightGBM Feature Importances.

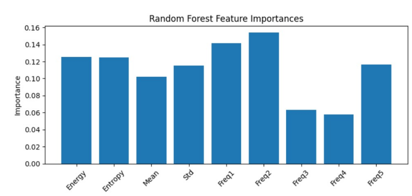

Fig. 7. Random Forest Feature Importances.

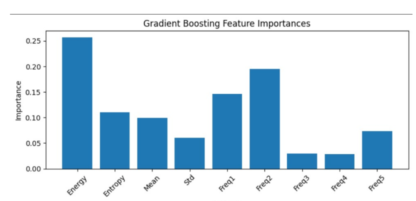

Fig. 8. Gradient Boosting Feature Importances.

E. Limitations

Despite promising results, the method has certain limitations:

- **Misclassification in Subtle Cases:** Images with very subtle abnormalities may be misclassified, possibly due to class imbalance or insufficient data variability.
- **Resource Constraints:** For implementation in portable or embedded systems, model compression or feature reduction strategies may be necessary.

V. Conclusion

This study introduces a lightweight and efficient method for classifying brain MRI images by combining image enhanced preprocessing with frequency-domain feature extraction using the Fast Fourier Transform (FFT). It extracts important statistical features such as energy, entropy, and dominant frequencies from the scans, helping to capture critical brain tissue patterns related to abnormalities.

These features are then used with advanced machine learning models, including XGBoost, LightGBM, and a hybrid of Random Forest and Gradient Boosting. Among all models, XGBoost achieved the highest classification accuracy, followed closely by LightGBM and the hybrid model. Confusion matrix analysis further supported the reliability of the models, showing low misclassification rates and strong consistency in detecting tumor-related abnormalities.

In summary, the proposed approach is computationally efficient, explainable, and well-suited for real-time applications in resource-limited settings. Its modular structure allows easy integration into clinical decision-support tools, making it a practical solution for improving neuroimaging diagnostics. The method contributes to more accessible, scalable, and accurate brain MRI classification systems that can support healthcare professionals in early and reliable diagnosis.

VI. Future Work

While the current system demonstrates promising performance, several enhancements can be explored to further improve its applicability and robustness:

- **Multi-Class Classification:** Extend the binary classification framework to support *multi-class differentiation* among various tumor types (e.g., glioma, meningioma, pituitary adenoma), thereby increasing clinical relevance.

By addressing these directions, the proposed method can evolve into a more comprehensive, scalable, and clinically valuable tool for automated brain MRI analysis.

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