The Princeton Journal of Interdisciplinary Research
ISSN 3069-8200

Brain Tumor Classification in MRI Using Power Spectral Density and Spatial Autocorrelation Features

Naima Rechid (author)[1], Abida Toumi (author)[2], Khier Benmahammed (author)[3], Abdelmalik Taleb-Ahmed (author)[4], Ali Khelifa (author)[5]

[1]Faculty of Electrical Engineering, University of Science and Technology Houari Boumediene, Algiers, Algeria

[2]Faculty of Science and Technology, University of Mohamed Khidher, Biskra, Algeria

[3]Faculty of Electrical Engineering, University of Farhat Abbas, Setif, Algeria

[4]LAMIH UMR CNRS UVHC 8530, Le Mont Houy 59313, University of Polytechnique Hauts-de-France, Valenciennes, France

[5]Faculty of Science and Technology, University of Mohamed Khidher, Biskra, Algeria

Abstract

Brain tumors represent a complex pathology characterized by abnormal cell growth in the brain and exhibit varying levels of aggressiveness depending on their tumor grade. Magnetic Resonance Imaging (MRI) is the reference modality for brain tumor diagnosis, providing detailed information about tissue morphology and heterogeneity. In this context, image-based feature analysis provides quantitative tools to extract informative descriptors for tumor characterization and classification.

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ISSN 3069-8200

This study proposes a feature-based methodology that exploits the space–frequency duality of MRI images to analyze tumor heterogeneity. Frequency-domain features are extracted from the Power Spectral Density (PSD), while spatial descriptors based on autocorrelation characterize the structural organization of tumor tissues. The combination of spectral and spatial features provides a multiscale representation of tumor heterogeneity.

Using Support Vector Machine SVM and Random Forest RF classifiers, PSD features achieve strong performance, with AUC values of 0.886, 0.904, 0.978, and 0.959 for SVM and 0.930, 0.957, 0.999, and 0.983 for RF across glioma, meningioma, no tumor, and pituitary classes. In contrast, autocorrelation features show lower performance with SVM, with an AUC of 0.861, but improve with RF, with an AUC of 0.947.

The fusion of PSD and autocorrelation features improves classification performance. Using SVM, AUC values reach 0.899, 0.905, 0.988, and 0.971, while RF achieves 0.927, 0.940, 0.997, and 0.984 for glioma, meningioma, no tumor, and pituitary classes. These results show that frequency-domain descriptors are highly discriminative, while combining spectral and spatial information improves the robustness of MRI tumor classification for computer-aided diagnosis.

Keywords: MRI, power spectral density, autocorrelation, classification

Introduction

According to a new analysis (Fink et al., 2026) from the World Health Organization (WHO) and the International Agency for Research on Cancer (IARC), cancer remains a cause major morbidity in the world, largely attributable to risk factors modifiable. The results

indicate that up to four out of ten cancer cases could be avoided on a global scale This study focuses on 30 preventable causes of cancer, including the smoking, alcohol consumption, overweight, physical inactivity, air pollution, the ultraviolet radiation and, for the first time, nine infectious agents. The estimates from the GLOBOCAN database indicate that a significant proportion of deaths related to cancer could be avoidable thanks to early detection and appropriate management and personalized (Sung et al., 2021).

Brain tumors represent a complex cancerous pathology characterized by an anomaly in cell growth in the brain. They can be benign, to slow evolution, or malignant, presenting an aggressive and invasive behavior. Their grade tumoral, defined according to the classification of the World Health Organization (WHO), constitutes a key indicator of their aggressiveness, distinguishing low grades (I–II) with slow growth from high grades (III–IV), of which glioblastoma represents the most severe form (WHO, 2021).

In this context, magnetic resonance imaging (MRI) constitutes the modality reference for the exploration of brain tumors. It allows a characterization detailed of the morphology and properties of brain tissues, playing an essential role in diagnosis, tumor stratification, therapeutic planning and clinical follow-up patients (Louis et al., 2021).

The complexity of brain tumors requires advanced quantitative methods to exploit MRI images. Radiomics allows extracting features describing the heterogeneity of tumor tissues, beyond visual analysis. This information is related to the tumor grade and the biological aggressiveness of the tumor.

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ISSN 3069-8200

Radiomics allows transforming MRI images into quantitative descriptors exploitable for tumor classification. In this context, the duality space–frequency, based on the Fourier transform, constitutes a relevant approach to analyze the textural variations associated with different tumor grades and characterize the structures tumours at different scales.

Frequency analysis based on the power spectral density (DSP) allows to characterize the distribution of energy according to spatial frequencies. Tumors from high grade, more heterogeneous and disorganized, generally present a dominance of high frequencies, while low-grade tumors concentrate their energy more in the low frequencies. Indicators such as the dominant frequency and spectral entropy can thus reflect the degree of tumor aggression.

In addition, spatial autocorrelation allows quantifying the organization structural of tumor tissues from the regularity and correlation length of textural patterns. Low-grade tumors generally exhibit a more regular, unlike high-grade tumors characterized by a loss of regularity and a rapid decrease in autocorrelation.

The combination of frequency and spatial descriptors thus offers a representation multi-scale of tumor heterogeneity, improving discrimination between grades tumors and constituting a relevant basis for the development of models of machine learning applied to the analysis of MRI images. The objective of this work is to evaluate the contribution of space-frequency duality for the multiclass classification of brain tumors from MRI images, by analyzing the complementary contribution of frequency (DSP) and spatial descriptors (autocorrelation)

In the extraction of radiomic signatures related to tumor grade, in order to propose a robust and interpretable methodology for diagnostic assistance. The classification of brain tumors from MRI images was the subject of numerous works. The first approaches were based on manual extraction of textural, statistical or morphological features, combined with classifiers classics such as SVM, Naïve Bayes, k-NN or random forests in order to distinguish the normal and pathological tissues or to estimate the tumor grade (Zhang et al., 2011, 2016; Gupta & Khanna, 2017; Amin et al., 2017).

With the rise of deep learning, convolutional neural networks (CNN) and their variants, such as U-Net or DeepMedic, allowed to learn automatically discriminative representations from MRI images, enhancing significantly the performances in segmentation and classification, notably on the BRATS database (Pereira et al., 2016; Havaei et al., 2017; Kamnitsas et al., 2017).

More recently, hybrid and multimodal approaches integrating learning by transfer, the fusion of MRI sequences, attention mechanisms, learning based on the graphs, generative antagonistic networks or even federated learning have been proposed in order to improve accuracy, robustness and the ability to generalize models (Hao et al., 2021; Kang et al., 2021; Ullah et al., 2024; Albalawi, 2024; Gencer and al., 2025). Despite these advances, several challenges persist, notably the reliable detection of small lesions, the precise segmentation of tumor regions and the need to develop lighter models, interpretable and easily integrable in clinical practice (Liu and al., 2020; Deb & Roy, 2021).

The proposed methodology is based on a radiomic approach applied to brain MRI images to extract textural descriptors that enable the distinction between healthy and

pathological images and the analysis of tumor grade (low-grade or high-grade). It relies on the exploitation of space–frequency duality, a fundamental principle of signal processing.

The main methodological steps are as follows:

• Frequency texture descriptors extracted from the Power Spectral Density (PSD) are used to characterize the distribution of energy across spatial frequencies and quantify texture granularity and heterogeneity (spectral energy, dominant frequency, spectral entropy).

• Spatial analysis based on autocorrelation is performed to characterize the structural organization of tumor tissues from the spatial dependence of intensities, using descriptors such as correlation length, spatial regularity, and anisotropy.

• Fusion of spatial and spectral descriptors is applied to obtain a multiscale representation of tumor heterogeneity from both structural and textural perspectives.

Based on the space–frequency duality, classification models, namely Support Vector Machine (SVM) and Random Forest (RF), are used to distinguish healthy from pathological MRI images and to identify tumor grades (low-grade and high-grade).

This approach exploits the complementary spatial and frequency information contained in MRI images in order to develop robust, interpretable, and clinically relevant classification models.

This article is organized as follows. The theoretical framework concerning DSP and autocorrelation is presented in Section II. Section III describes the proposed approach of frequency and spatial analysis for classification, while the experimental results are presented

and discussed in the Section IV. Finally, the conclusions and prospects for future work are set out in Section V.

The Theoretical Framework

Space–frequency duality in MRI imaging

Magnetic resonance imaging (MRI) is inherently acquired in the frequency domain (*k*-space), and spatial images are reconstructed using an inverse two-dimensional Fourier transform, establishing a fundamental link between spatial structures and frequency content. In this work, this property is exploited to derive complementary descriptors for tumor characterization and classification. Specifically, frequency-domain analysis based on power spectral density (PSD) is used to capture spectral texture information, while spatial autocorrelation analysis characterizes spatial dependencies within MRI images.

Frequency-domain analysis and power spectral density

The frequency representation of MRI images is obtained using the two-dimensional discrete Fourier transform (2D-DFT). The power spectral density (PSD), defined as the squared magnitude of the Fourier coefficients, describes the distribution of signal energy across spatial frequencies. From the PSD, several spectral descriptors are derived, including total spectral energy, second-order spectral moment, spectral entropy, and frequency anisotropy.

Fourier Transform and Relationship with k-Space

In Magnetic Resonance Imaging (MRI), acquired data are collected in the frequency domain (k-space), which represents the Fourier transform of the spatial distribution of the MR signal. The spatial image $I(x, y)$ is converted into its frequency representation $X(k_x, k_y)$using the two-dimensional Discrete Fourier Transform (2D-DFT).

$$X(k_x, k_y) = \sum_{x=0}^{N-1} \sum_{y=0}^{M-1} I(x, y)\ e^{-i2\pi\left(\frac{k_x x}{N} + \frac{k_y y}{M}\right)}$$

In k-space, low frequencies (center) describe the global contrast and overall structure of the image, while high frequencies (periphery) encode fine anatomical details and edges.

Power Spectral Density

The Power Spectral Density (PSD) describes the distribution of signal energy across spatial frequencies and is defined as:

$$S_X(k_x, k_y) = \left|X(k_x, k_y)\right|^2$$

A normalized PSD can be obtained by dividing by the total spectral energy. This representation provides a quantitative description of frequency content, where low frequencies correspond to global structures and high frequencies capture fine textural variations in MRI images.

PSD-Based Feature Extraction

To exploit the information contained in k-space, several spectral descriptors are extracted from the 2D PSD. These features quantify the distribution of spectral energy and provide compact representations of MRI image texture suitable for classification tasks.

Spatial autocorrelation analysis

To complement spectral information, spatial organization is analyzed using the two-dimensional autocorrelation function, derived from the PSD through the Wiener–Khinchin theorem. This function measures similarity between pixels as a function of spatial distance. Key spatial descriptors include correlation length, FWHM, autocorrelation variance, and spatial anisotropy, which characterize structural coherence within the tumor.

Spatial Autocorrelation Function

A fundamental relationship links the PSD to the two-dimensional spatial autocorrelation function of the image through the Wiener–Khinchin theorem. The spatial autocorrelation function $R_X(\tau_x, \tau_y)$is defined as the inverse Fourier transform $\mathcal{F}^{-1}$ of the power spectral density:

$$R_X(\tau_x, \tau_y) = \mathcal{F}^{-1}[S_X(k_x, k_y)]$$

which can be written as: $R_X(\tau_x, \tau_y) = \sum_{k_x=0}^{N-1} \sum_{k_y=0}^{M-1} S_X(k_x, k_y)\ e^{i2\pi\left(\frac{k_x\tau_x}{N}+\frac{k_y\tau_y}{M}\right)}$

For texture analysis, the autocorrelation function is commonly normalized:

$$R_{nX}(\tau_x, \tau_y) = \frac{R_X(\tau_x, \tau_y)}{R_X(0,0)}$$

The value $R_X(0,0)$ corresponds to the total spectral energy of the signal (Gonzalez & Woods, 2018). The spatial autocorrelation function describes the degree of similarity between pixels separated by a given spatial distance, making it a powerful tool for extracting spatial texture descriptors.

Spatial Descriptors Derived from the Autocorrelation Function

The spatial autocorrelation function is a fundamental tool for **texture analysis in MRI images**, as it quantifies the similarity between pixel intensities separated by spatial shifts and provides information about the structural organization of tissues (Haralick, Shanmugam, & Dinstein, 1973; Gonzalez & Woods, 2018).

From this function, several spatial descriptors can be derived to characterize the scale, homogeneity, and complexity of anatomical structures. These descriptors are widely used in radiomics-based MRI analysis and can serve as input variables for automatic tumor classification models (Gillies, Kinahan, & Hricak, 2016).

Approach of frequency and spatial analysis for MRI classification

Brain MRI Dataset

The dataset used in this study is the Brain Tumor MRI Dataset available on Kaggle (Nickparvar, 2021). It contains 7,023 human brain MRI images divided into four classes: glioma, meningioma, pituitary tumor, and no tumor. Gliomas correspond to the most aggressive tumors, while meningiomas are generally benign (Grade I–II) and pituitary tumors are typically low-grade benign adenomas.

The dataset is divided into training (≈80%, 5,712 images) and testing (≈20%, 1,311 images) sets, each organized into four class folders. Images are provided in .jpg format, resized to 256 × 256 pixels, and converted to grayscale. The dataset includes axial, coronal, and sagittal slices, enabling the evaluation of frequency-domain (PSD) and spatial (autocorrelation) features for brain MRI classification.

PSD-Based Classification Strategy for MRI

The proposed pipeline for MRI image classification relies on frequency-domain analysis based on the Power Spectral Density (PSD). It consists of the following steps:

Step 1: Image Preprocessing

MRI images are normalized to reduce acquisition-related intensity variations and artifacts, preparing them for classification.

Step 2: Power Spectral Density Computation

The Power Spectral Density (PSD) is then computed to obtain the distribution of signal energy in the frequency domain.

Step 3: Spectral Feature Extraction

Several spectral descriptors are extracted from the PSD. These features include total spectral energy, second-order spectral moment, root mean square spatial frequency, spectral entropy, radial spectral profile, dominant frequency, frequency anisotropy (Stoica & Moses, 2005; Kushner et al., 2023). The resulting vector is used by a supervised classifier to distinguish healthy tissues from low-grade and high-grade tumors.

Step 4: PSD Classification

The PSD-based feature vector is used as input to classifiers to distinguish healthy MRI images (no tumor) from pathological images and to identify tumor grades (low-grade and high-grade). The Support Vector Machine (SVM) and Random Forest (RF), exploit spectral texture information to improve the automatic classification of brain MRI images.

MRI Classification Strategy Based on Autocorrelation

The classification of MRI images based on the autocorrelation function relies on the analysis of the spatial properties of tissue structures. The proposed classification pipeline includes the following main steps.

Step 1: Image Preprocessing

MRI images are first normalized in order to reduce intensity variations related to acquisition conditions.

Step 2: Autocorrelation Function Computation

The spatial autocorrelation function is computed to characterize the similarity between pixels as a function of spatial distance. This representation allows the analysis of the spatial organization and scale of structures present in the image.

Step 3: Extraction of Spatial Descriptors

Spatial descriptors derived from the autocorrelation function (Guan et al., 2004; Wöhler, 2013) are used to build a spatial feature vector describing tissue organization. These

features include correlation length, full width at half maximum (FWHM), integral correlation length, mean correlation radius, spatial correlation variance, spatial entropy, spatial anisotropy, structural regularity index, These features form a spatial descriptor vector describing the scale, homogeneity, and complexity of tissue structures. The resulting vector is used by a supervised classifier to distinguish healthy tissues from low-grade and high-grade tumors.

Step 4: Autocorrelation-Based Classification

The autocorrelation-based feature vector is used as input to a classifier to distinguish healthy MRI images (no tumor) from pathological images, and to identify tumor grades (low-grade and high-grade). The Support Vector Machine (SVM) and Random Forest (RF), exploit spectral texture information to improve the automatic classification of brain MRI images.

Feature Fusion Strategy for MRI Tumor Classification

Spectral and spatial features are combined using feature-level fusion, where both sets of features are concatenated into a single vector. This strategy exploits the complementary nature of frequency-domain energy distribution and spatial correlation patterns. It enables a more comprehensive representation of tumor heterogeneity. The Support Vector Machine (SVM) and Random Forest (RF), exploit spectral texture information to improve the automatic classification of brain MRI images.

Results and Discussion

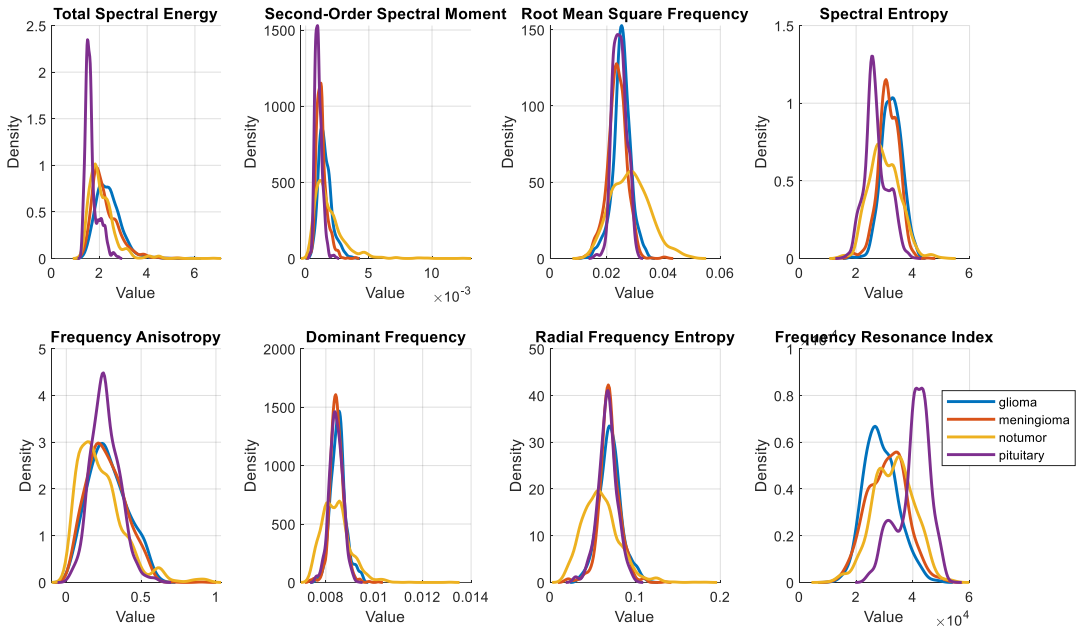
Comparative Analysis of Frequency and Spatial Features for Brain MRI Classification

The Princeton Journal of Interdisciplinary Research
ISSN 3069-8200

As shown in Figure 1, frequency-domain features were extracted from the Power Spectral Density (PSD) of MRI images to analyze the distribution of image energy in the frequency domain, providing relevant information about the textural characteristics of brain tissues.

Figure 1

Frequency-Domain Features Extracted from the Power Spectral Density (PSD)



The histogram distributions for the four classes (glioma, meningioma, pituitary tumor, and no tumor) reveal noticeable differences in their spectral characteristics. Images from the no-tumor class generally exhibit a smoother and more concentrated frequency distribution, reflecting the relatively homogeneous texture of normal brain tissue. In contrast, tumor

classes show broader and more dispersed spectral distributions due to the structural alterations induced by abnormal tissue growth.

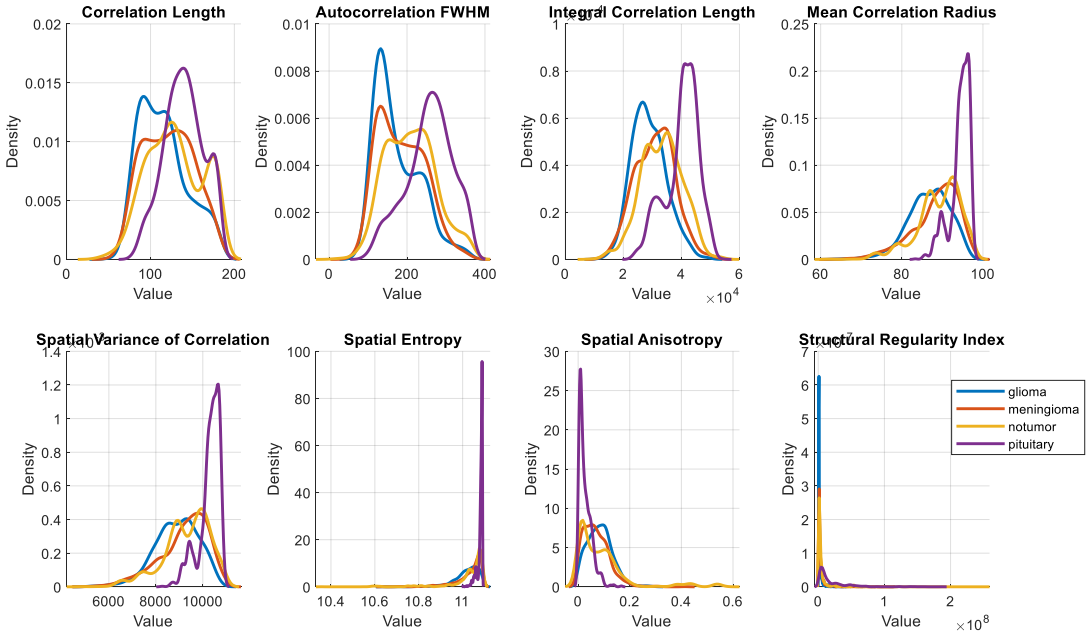
These variations are also related to the biological behavior of the tumors. Gliomas, which are typically the most aggressive brain tumors, often present highly heterogeneous textures and complex spectral patterns. Meningiomas, usually benign and less invasive, tend to produce more moderate spectral variations. Pituitary tumors, which are predominantly benign and localized, frequently show distinct spectral peaks associated with their compact structure. Therefore, PSD-based features provide discriminative information for distinguishing normal brain tissue from tumorous regions.

As shown in Figure 2, spatial features were extracted using autocorrelation analysis, which evaluates the statistical relationship between neighboring pixels within MRI images. This approach characterizes texture regularity and spatial repetition patterns, providing relevant information about the structural organization of brain tissues.

Figure 2

Spatial Features Extracted Using Autocorrelation

The Princeton Journal of Interdisciplinary Research
ISSN 3069-8200

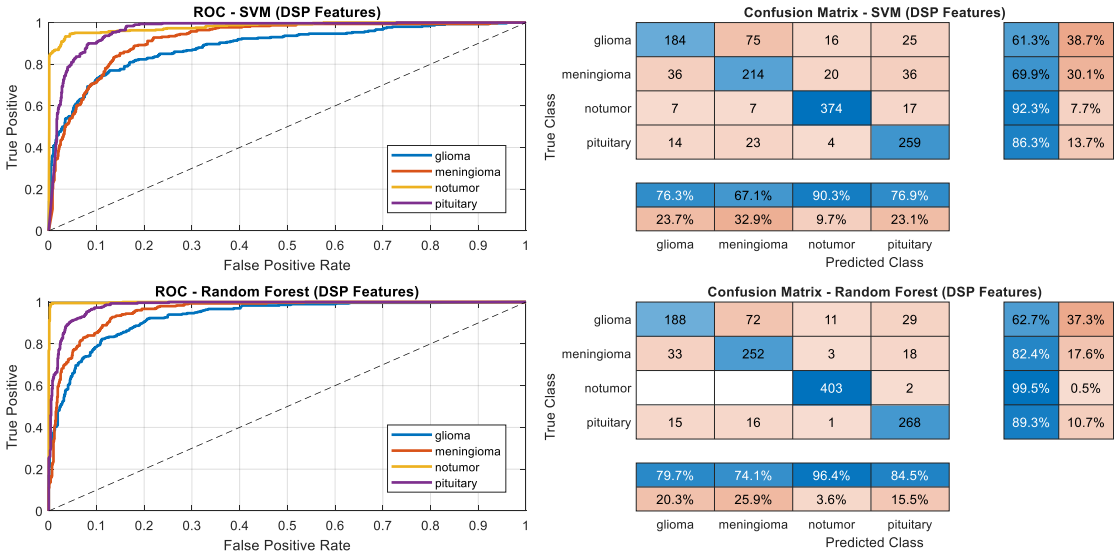


The distributions of autocorrelation features reveal distinct behaviors across the four classes (glioma, meningioma, pituitary tumor, and no tumor). The no-tumor class shows stable and consistent autocorrelation values, reflecting the relatively uniform structure of healthy brain tissue. In contrast, the glioma class, which represents the most aggressive tumors, exhibits greater variability and dispersion in autocorrelation values, indicating strong spatial heterogeneity caused by invasive tumor growth. Meningiomas, which are generally low-grade and often benign, present moderate variations in autocorrelation patterns . The pituitary tumor class, considered the least aggressive and typically benign, tends to show more localized and relatively structured spatial patterns due to its compact nature.

Consequently, autocorrelation-based features effectively capture spatial irregularities and structural variations associated with tumor regions, providing complementary information for MRI tumor characterization.

Figure 3

ROC Curves and Confusion Matrices for MRI Classification Using PSD Features

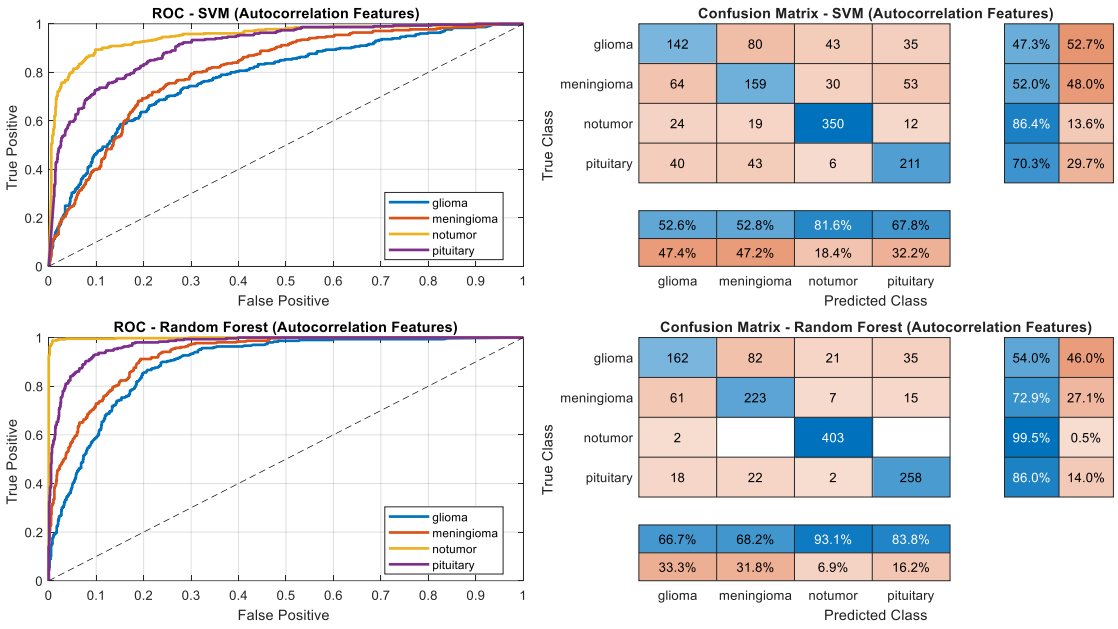


As shown in Figure 3, the ROC curves and confusion matrices obtained using PSD-based features with SVM and Random Forest (RF) demonstrate strong discriminative performance for the four classes. The ROC curves are close to the upper-left corner, with RF slightly outperforming SVM. The no-tumor class achieves the highest accuracy due to the homogeneous texture of healthy tissues, while some confusion occurs between glioma and meningioma because of similarities in their spectral texture patterns.

As shown in Figure 4, the results obtained using autocorrelation features show moderate discriminative performance compared with PSD descriptors. RF again performs better than SVM, reducing several misclassifications. The no-tumor class remains the easiest to identify, whereas glioma and meningioma exhibit greater confusion due to similarities in their spatial texture structures.

Figure 4

ROC Curves and Confusion Matrices for MRI Classification Using Autocorrelation Features

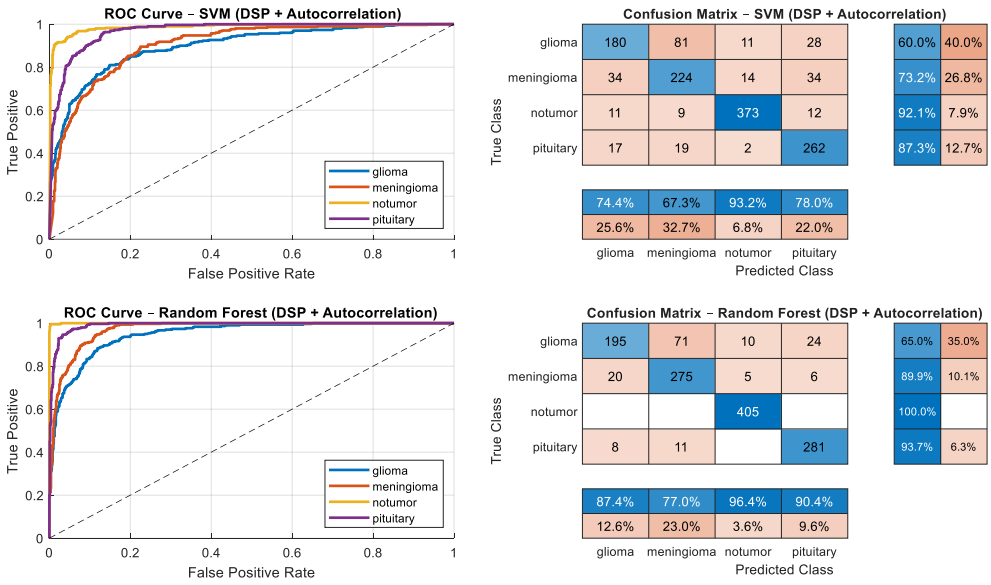


As shown in Figure 5, the combination of PSD and autocorrelation features improves classification performance. The ROC curves move closer to the upper-left corner, and RF achieves the best results with fewer misclassifications. Overall, the fusion of frequency and

spatial descriptors provides a more comprehensive representation of MRI textures, leading to more robust brain tumor classification.

Figure 5

ROC Curves and Confusion Matrices for MRI Classification Using PSD and Autocorrelation Features



Comparative Analysis of PSD and Autocorrelation Features for MRI Classification

As shown in Table 1, PSD features alone already provide strong performance for MRI classification. With SVM, the AUC (Area Under the ROC Curve) values reach 0.886 (glioma), 0.904 (meningioma), 0.978 (no tumor), and 0.959 (pituitary). The performance further improves with Random Forest, achieving 0.930, 0.957, 0.999, and 0.983, respectively. These results indicate that frequency-domain descriptors effectively capture the spectral

energy distribution associated with tumor textures. This is particularly relevant for gliomas, the most aggressive brain tumors, which often exhibit highly heterogeneous textures due to rapid and invasive growth.

Using autocorrelation features alone results in lower performance, especially with SVM, where AUC values are 0.784 (glioma), 0.806 (meningioma), 0.947 (no tumor), and 0.906 (pituitary), corresponding to a macro AUC of 0.861. With Random Forest, the results improve (0.891, 0.926, 0.998, and 0.973; macro AUC = 0.947). These results suggest that spatial descriptors mainly capture the structural organization of tissues. Such information is useful for characterizing tumors like meningiomas, which are generally low-grade (mostly Grade I) and often benign, showing more regular spatial patterns than highly aggressive tumors.

Table 1

Comparison of AUC Scores for Brain MRI Tumor Classification

Method	**Glioma**	**Meningioma**	**No Tumor**	**Pituitary**
SVM (PSD)	0.886	0.904	0.978	0.959
RF (PSD)	0.930	0.957	0.999	0.983
SVM (Autoc)	0.784	0.806	0.947	0.906
RF (Autoc)	0.891	0.926	0.998	0.973
SVM (PSD + Autoc)	0.899	0.905	0.988	0.971

RF (PSD + Autoc)	0.927	0.940	0.997	0.984

Finally, the fusion of PSD and autocorrelation features improves overall performance by combining frequency and spatial information. With SVM, the AUC values are 0.899, 0.905, 0.988, and 0.971, while Random Forest achieves 0.927, 0.940, 0.997, and 0.984 for glioma, meningioma, no tumor, and pituitary, respectively. This combination provides a more comprehensive multi-scale representation of tumor heterogeneity, which is particularly useful for distinguishing tumors with different biological behaviors. For instance, pituitary tumors, which are the least aggressive and typically benign adenomas, usually present more localized and structured patterns that can be effectively captured when spatial and frequency information are combined.

Conclusion

This study addressed the problem of Brain Tumor Classification in MRI Using Power Spectral Density and Spatial Autocorrelation Features by exploiting the space–frequency duality of MRI images. The proposed methodology is based on a feature analysis approach applied to brain MRI images to extract textural descriptors that enable the distinction between healthy and pathological tissues and support tumor grade analysis.

Frequency-domain descriptors derived from the Power Spectral Density (PSD) and spatial features based on autocorrelation analysis were extracted to characterize tumor heterogeneity and the structural organization of brain tissues. The experimental results show that PSD-based features provide strong discriminative capability, particularly when combined

with the Random Forest classifier, achieving high AUC (Area Under the ROC Curve) values across the four classes: glioma, meningioma, pituitary tumor, and no tumor. In contrast, autocorrelation descriptors alone exhibit lower performance, although they still capture relevant spatial dependencies within tumor structures. The fusion of PSD and autocorrelation features further improves classification performance by providing a multiscale representation of tumor textures and spatial patterns.

The main contributions of this work can be summarized as follows:

- Development of a feature-based framework for brain tumor classification in MRI using complementary spectral and spatial descriptors.
- Extraction of frequency-domain features based on Power Spectral Density to characterize tumor texture heterogeneity.
- Integration of spatial descriptors derived from autocorrelation to capture the structural organization of brain tissues.
- Fusion of spectral and spatial features to enhance classification robustness and performance.

Overall, the proposed approach demonstrates that combining frequency-domain and spatial descriptors is an effective strategy for MRI-based brain tumor classification and can contribute to the development of robust and interpretable computer-aided diagnosis systems for clinical decision support. Future work will focus on integrating additional texture descriptors, advanced machine learning and deep learning techniques, as well as multimodal MRI data to further improve classification accuracy and robustness. In addition, larger and

more diverse datasets will be investigated to enhance the generalizability of the proposed framework for clinical applications.

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