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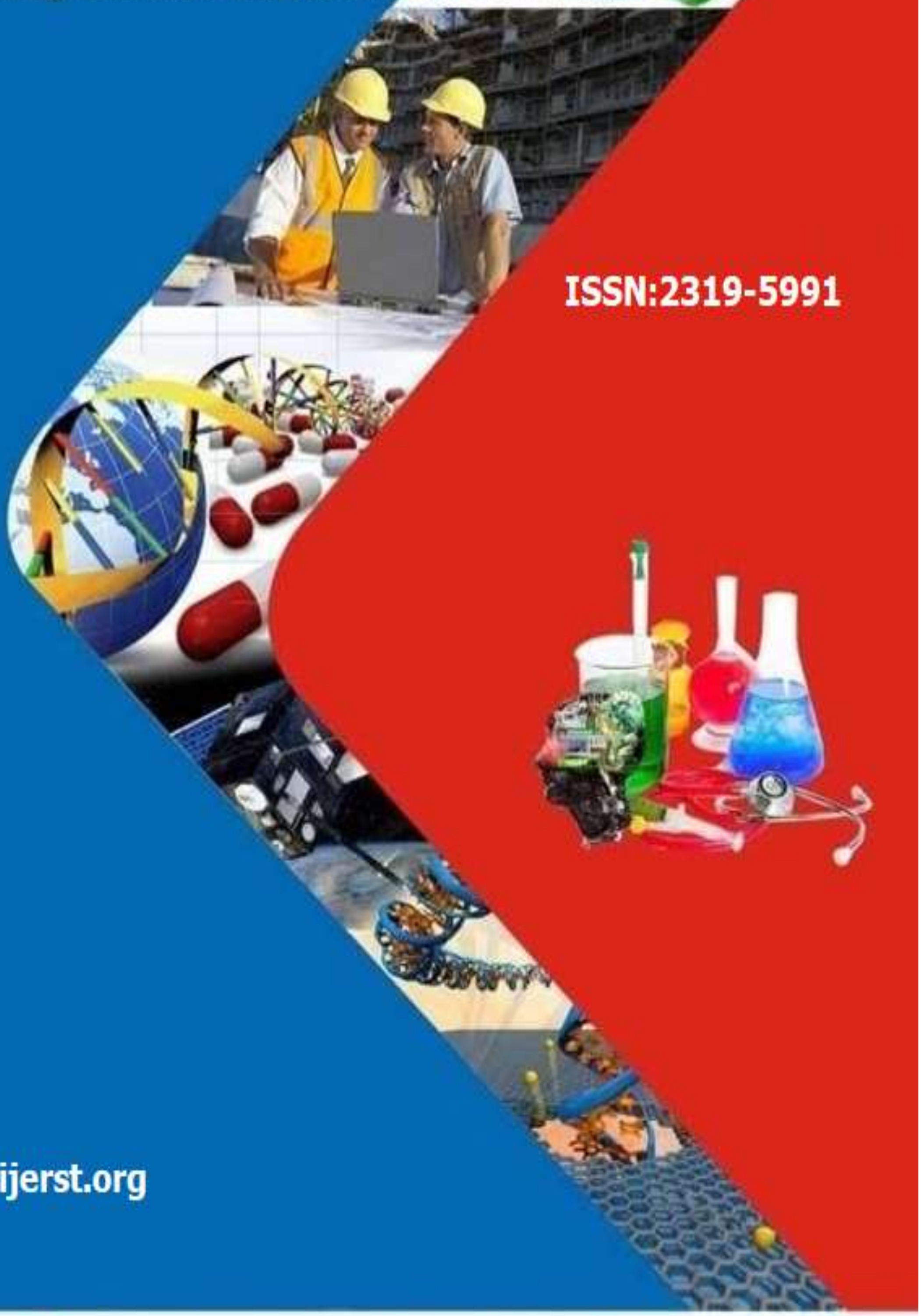

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MACHINE LEARNING-BASED CANCER CLASSIFICATION IN MEDICAL IMAGING DATA

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ABSTACT

Brain tumor classification from magnetic resonance imaging (MRI) data is crucial for accurate diagnosis and treatment planning in clinical practice. Accurate and timely tumor classification enables clinicians to determine appropriate treatment strategies, monitor disease progression, and assess treatment response effectively. Moreover, machine learning models can assist radiologists in interpreting MRI images, reducing interpretation errors and improving diagnostic accuracy. Additionally, brain tumor classification supports research efforts aimed at understanding tumor biology, identifying biomarkers, and developing targeted therapies for different tumor subtypes. Existing methods for brain tumor classification from MRI data often rely on manual segmentation and feature extraction, which can be labor-intensive and prone to variability. These methods may struggle to capture subtle differences in tumor morphology or texture, leading to inaccuracies in classification. Moreover, traditional approaches may require expertise in radiology and medical imaging, limiting their accessibility and scalability in clinical settings. Additionally, manual feature engineering may overlook important tumor characteristics or fail to exploit the full potential of MRI data for classification purposes. The proposed system utilizes machine learning techniques to automate and enhance brain tumor classification from MRI image data, addressing the limitations of existing methods. This work employs machine learning models to learn discriminative features directly from MRI images. By training models on large-scale MRI datasets annotated with tumor labels, the propsoed models can effectively differentiate between different tumor types and accurately classify brain tumors into relevant categories.

Keywords: Cancer Classification, Machine Learning, Random Forest Classifier, MRI, SVM, Brain tumor.

1.INTRODUCTION

In the realm of medical imaging, the classification of brain tumors from MRI data is a pivotal component of diagnosis and treatment planning. However, traditional methods often rely on manual segmentation and feature extraction, which can be time-consuming and subject to human error. This abstract introduces a novel approach leveraging machine learning techniques to automate and enhance the classification process, addressing the limitations of existing methods. By training machine learning models on large-scale MRI datasets annotated with tumor labels, this system aims to discern subtle differences in tumor morphology and texture, thus improving classification accuracy. The proposed methodology bypasses the need for manual feature engineering, instead allowing models to learn discriminative features directly from the MRI images themselves. This shift not only streamlines the classification process but also has the potential to uncover previously overlooked tumor characteristics, thereby enhancing diagnostic capabilities.

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2. LITERATURE SURVEY

In the human body, the brain is an enormous and complex organ that controls the whole nervous system, and it contains around 100-billion nerve cells [1]. This essential organ is originated in the center of the nervous system. Therefore, any kind of abnormality that exists in the brain may put human health in danger. Among such abnormalities, brain tumors are the most severe ones. Brain tumors are uncontrolled and unnatural growth of cells in the brain that can be classified into two groups such as primary tumors and secondary tumors. The primary tumors present in the brain tissue, while the secondary tumors expand from other parts of the human body to the brain tissue through the bloodstream [2]. Among the primary tumors, glioma and meningioma are two lethal types of brain tumors, and they may lead a patient to death if not diagnosed at an early stage [3]. In fact, the most common brain tumor in humans is glioma [4].

According to the World Health Organization (WHO), brain tumors can be classified into four grades [1]. The grade 1 and grade 2 tumors describe lower-level tumors (e.g., meningioma), while grade 3 and grade 4 tumors consist of more severe ones (e.g., glioma). In clinical practice, the incidence rates of meningioma, pituitary, and glioma tumors are approximately 15%, 15%, and 45%, respectively.

There are different ways to treat brain tumors depends on the tumor location, size, and type. Presently, the most common treatment for brain tumors is surgery as it has no side effects on the brain [5]. Different types of medical imaging technologies such as computed tomography (CT), positron emission tomography (PET), and magnetic resonance imaging (MRI) are available that are used to observe the internal parts of the human body conditions. Among all these imaging modalities, MRI is considered most preferable as it is the only non-invasive and non-ionizing modality that offers valuable information in 2D and 3D formats about brain tumor type, size, shape, and position [6]. However, manually reviewing these images is time-consuming, hectic, and even prone to error due to the influx of patients [7]. To address this problem, the development of an automatic computer-aided diagnosis (CAD) system is required to alleviate the workload of the classification and diagnosis of brain MRI and act as a tool for helping radiologists and doctors.

Several efforts have been made to develop a highly accurate and robust solution for the automatic classification of brain tumors. However, due to high inter and intra shape, texture, and contrast variations, it remains a challenging problem. The traditional machine learning (ML) techniques rely on handcrafted features, which restrains the robustness of the solution. Whereas the deep learning-based techniques automatically extract meaningful features which offer significantly better performance. However, deep learning-based techniques require a large amount of annotated data for training, and acquiring such data is a challenging task. To overcome these issues, in this study, we proposed a hybrid solution that exploits (1) various pre-trained deep convolutional neural networks (CNNs) as feature extractors to extract powerful and discriminative deep features from brain magnetic resonance (MR) images, and (2) various ML classifiers to identify the normal and abnormal brain MR images. Also, to investigate the benefits of combining features from different pre-trained CNN models, we designed the novel feature ensemble method for the MRI-based brain tumor classification task. We proposed the novel feature evaluation and selection mechanism where the deep features from 13 different pre-trained CNNs are evaluated using 9 different ML classifiers and selected based on our proposed feature selection criteria. In our proposed framework, we concatenated the selected top three deep features from three different CNNs to form a synthetic feature. The concatenation process integrates the information from different CNNs to create a more discriminative feature representation

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than using the feature extracted from a single CNN model since different CNN architectures can capture diverse information in brain MR images. An ensemble of deep features is then fed into several ML classifiers to predict the final output, whereas most of the previous works have employed traditional feature extraction techniques [8]. In our experiment, we provided an extensive evaluation using 13 different pre-trained deep convolutional neural networks and 9 different ML classifiers on three different datasets: (1) BT-small-2c, the small dataset with 2 classes (normal/tumor), (2) BT-large-2c, the large dataset with 2 classes (normal/tumor), and (3) the large dataset with 4 classes (normal, glioma tumor, meningioma tumor, and pituitary tumor) for brain tumor classification. Our experiment results demonstrate that the ensemble of deep features can help improving performance significantly. In summary, our contributions are listed as follows:

We designed and implemented a fully automatic hybrid scheme for brain tumor classification, which uses both (1) the pre-trained CNN models to extract the deep features from brain MR images and (2) ML classifiers to classify brain tumor type effectively.

We proposed a novel method which consists of three steps: (1) extract deep features using pre-trained CNN models for meaningful information extraction and better generalization, (2) select the top three performing features using fined-tuned several ML models for our task, and (2) combine them to build the ensemble model to achieve state-of-the-art performance for brain tumor classification in brain MR images.

We conducted extensive experiments on 13 different pre-trained CNN models and 9 different ML classifiers to compare the effectiveness of each pre-trained CNN model and each ML classifier on three different brain MRI datasets: (1) BT-small-2c, the small dataset with 2 classes (normal/tumor), (2) BT-large-2c, the large dataset with 2 classes (normal/tumor), and (3) the large dataset with 4 classes (normal, glioma tumor, meningioma tumor, and pituitary tumor) for brain tumor classification.

The layout of this study is organized as follows: The related work is given in Section 2. The proposed method is presented in Section 3. The experimental settings and results are shown in Section 4. The conclusion section is described in Section 5.

2.1 Related Work

The traditional ML methods are comprised of several steps: pre-processing, feature extraction, feature reduction, and classification. In traditional ML methods, feature extraction is a core step as the classification accuracy relies on extracted features. There are two main types of feature extraction. The first type of feature extraction is low-level (global) features, for instance, texture features and intensity, first-order statistics (e.g., mean, standard deviation, and skewness), and second-order statistics such as gray-level co-occurrence matrix (GLCM), wavelet transform (WT), Gabor feature, and shape. For instance, Selvaraj et al. [9] employed first-order and second-order statistics using least square support vector machine (SVM) and develop a binary classifier to classify the normal and abnormal brain MR images. John et al. [10] used GLCM and discrete wavelet transformation-based methods for tumor identification and classification. The low-level features represent the image efficiently; however, the low-level features and their representation capacity are limited since most brain tumors have similar appearances such as texture, boundary, shape, and size. Ullah et al. [8] extracted the approximation and detail coefficient of level-3 decomposition using DWT, reduced the coefficient by employing color moments (CM), and finally employed a feed-forward artificial neural network to identify the normal and abnormal brain MR images.

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The second type of feature extraction is the high-level (local) features, such as fisher vector (FV), scale-invariant feature transformation (SIFT), and bag-of-words (BoW). Different researchers have employed BoW for medical image retrieval and classification. Such as the classification of breast tissue density in mammograms [11], X-ray images retrieval and classification on pathology and organ levels [12], and content-based retrieval of brain tumor [13]. Cheng et al. [14] employed FV to retrieve the brain tumor. The statistical features extracted from SIFT, FV, and BoW are high-level features formulated on a local scale that does not consider spatial information. Hence, it is noticeable that in the traditional ML method, there are two main problems in the feature extraction stage. First, it only focuses on either high-level or low-level features. Second, the traditional ML method depends on handcrafted features, which need strong prior information such as the location or position of the tumor in an image, and there are high chances of human errors. Therefore, it is essential to develop a method to combine both high-level and low-level features without using handcrafted features.

Most of the existing works in medical MR imaging refers to automatic segmentation of tumor region. Recently, Numerous researchers have proposed different techniques to detect and segment the tumor region in MR images [15,16,17]. Once the tumor in MRI is segmented, these tumors need to be classified into different grades. In previous research studies, binary classifiers have been employed to identify the benign and malignant classes [8,18,19]. For instance, Ullah et al. [8] proposed a hybrid scheme for the classification of brain MR images into normal and abnormal using histogram equalization, Discrete wavelet transform, and feed-forward artificial neural network, respectively. Kharrat et al. [18] categorize the brain tumor into normal and abnormal using a genetic algorithm and support vector machine. Besides, Papageorgiou et al. [19] categorized the high-grade and low-grade gliomas based on fuzzy cognitive maps and attained 93.22% and 90.26% accuracy for high-grade and low-grade brain tumors, respectively.

Shree and Kumar [20] divided the brain MRI into two classes: normal and abnormal. They used GLCM for feature extraction, while a probabilistic neural network (PNN) classifier has been employed to classify the brain MR image into normal and abnormal and obtained 95% accuracy. Arunachalam and Savarimuthu [21] proposed a model to categorize the normal and abnormal brain tumor in brain MR images. Their proposed model comprised enhancement, transformation, feature extraction, and classification. First, they have enhanced the brain MR image using shift-invariant shearlet transform (SIST). Then, they extracted the features using Gabor, grey level co-occurrence matrix (GLCM), and discrete wavelet transform (DWT). Finally, these extracted features were then fed into feed-forward backpropagation neural network and obtained a high accuracy rate. Rajan and Sundar [22] proposed a hybrid energy-efficient method for automatic tumor detection and segmentation. Their proposed method is comprised of seven long phases and reported 98% accuracy. The main drawback of their proposed model is high computation time due to the use of numerous techniques.

Since the last decade, deep learning methods have been widely used for brain MRI classification [23,24]. The deep learning method does not need handcrafted (manually) extracted features as it embedded the feature extraction and classification stage in self-learning. The deep learning method requires a dataset where sometimes a pre-processing operation needs to be done, and then salient features are determined in a self-learning manner [25]. In MR imaging classification, a key challenge is to reduce the semantic gap between the high-level visual information perceived by the human evaluator and the low-level visual information captured by the MR imaging machine. To reduce the semantic gap, the convolutional neural networks (CNNs), one of the famous deep learning techniques

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for image data, can be used as a feature extractor to capture the relevant features for the classification task. Feature maps in the initial layers and higher layers of CNNs models extract low-level features and high-level content (domain) specific features, respectively. Feature maps in the earlier layer construct simple structural information, for instance, shape, textures, and edges, whereas higher layers combine these low-level features to construct (encode) efficient representation, which integrates global and local information.

Recently, different researchers have used CNNs for brain MRI classification and validated their proposed methodology on brain tumor classification datasets [26,27,28]. Deepak and Ameer [29] used a pre-trained GoogLeNet to extract features from brain MR images with deep CNN to classify three types of brain tumor and obtained 98% accuracy. Ahmet and Muhammad [30] used different CNN models such as GoogLeNet, Inception V3, DenseNet-201, AlexNet, and ResNet-50 to classify the brain MR images and obtained reasonable accuracies. They modified pre-trained ResNet-50 CNN by removing its last 5 layers and added new 8 layers, and obtained 97.2% accuracy with this model, which is the highest accuracy among all pre-trained models. Khwaldeh et al. [31] proposed a CNN model to classify the normality and abnormality of brain MR images as well as high-grade and low-grade glioma tumors. They have modified the AlexNet CNN model and used it as their network architecture, and they obtained 91% accuracy. Despite the valuable works being done in this area, developing a robust and practical method still requires more effort to classify brain MR images. Saxena et al. [32] used Inception V3, ResNet-50, and VGG-16 models with transfer learning methods to classify brain tumor data. The ResNet-50 model obtained the highest accuracy rate with 95%. In studies [33,34] CNN architectures have been introduced to classify brain tumors. In these architectures, the convolution neural network extracts the features from brain MRI using convolution and pooling operations. The main purpose of these proposed models is to find the best deep learning model that accurately classifies the brain MR images. Francisco et al. [35] presented a multi-pathway CNN architecture for automatic brain tumor segmentation such as glioma, meningioma, and pituitary tumor. They have evaluated their proposed model using a publicly available T1-weighted contrast-enhanced MRI dataset and obtained 97.3% accuracy. However, their training procedure is quite expensive. Raja et al., [36] proposed a hybrid deep autoencoder (DAE) for brain tumor classification using the Bayesian fuzzy clustering (BFC) approach. Initially, they have used a non-local mean filter to remove the noise from the image. Then the BFC approach is employed for brain tumor segmentation. Furthermore, some robust features were extracted using scattering transform (ST), information-theoretic measures, and wavelet packet Tsallis entropy (WPTE). Eventually, a hybrid scheme of DAE is employed for brain tumor classification and achieved high accuracy.

3. PROPOSED METHODOLOGY

This research embarks on a journey to revolutionize brain tumor classification from magnetic resonance imaging (MRI) data, recognizing its pivotal role in the realm of clinical practice. With precision and timeliness at the forefront, accurate tumor classification empowers clinicians to chart appropriate treatment strategies, monitor disease trajectories, and evaluate treatment efficacy with greater effectiveness. Harnessing the power of machine learning, this endeavor aims to equip radiologists with tools that augment their expertise, mitigating interpretation errors and enhancing diagnostic accuracy. Beyond the clinic, brain tumor classification serves as a linchpin for advancing our understanding of tumor biology, pinpointing biomarkers, and tailoring targeted therapies for diverse tumor subtypes.

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In navigating the landscape of existing methodologies, the research confronts the limitations inherent in manual segmentation and feature extraction techniques. These labor-intensive processes, prone to variability, often struggle to capture the subtleties of tumor morphology or texture, resulting in classification inaccuracies. The expertise required in radiology and medical imaging confines the accessibility and scalability of traditional approaches within clinical settings. Compounded by the risk of overlooking crucial tumor characteristics, manual feature engineering may fall short in harnessing the full spectrum of information embedded within MRI data for classification purposes.

To transcend these challenges, the research introduces a paradigm shift through the integration of machine learning techniques. By leveraging machine learning models to glean discriminative features directly from MRI images, the proposed system endeavors to automate and elevate brain tumor classification. Grounded in the richness of large-scale MRI datasets annotated with tumor labels, these models are poised to discern nuances between different tumor types and classify brain tumors with unprecedented accuracy.

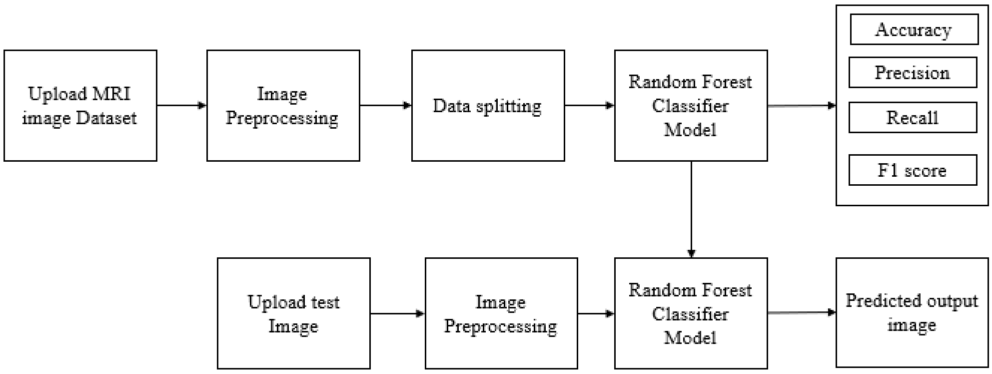

Fig. 1: Proposed block diagram of system architecture.

In weaving together these intricately orchestrated steps, the research endeavors to propel the field of brain tumor classification forward, offering a pathway to enhanced clinical decision-making and accelerated research breakthroughs in oncology.

3.1 Random Forest Classifier

Random Forest is a popular machine learning algorithm that belongs to the supervised learning technique. It can be used for both Classification and Regression problems in ML. It is based on the concept of ensemble learning, which is a process of combining multiple classifiers to solve a complex problem and to improve the performance of the model. As the name suggests, "Random Forest is a classifier that contains a number of decision trees on various subsets of the given dataset and takes the average to improve the predictive accuracy of that dataset." Instead of relying on one decision tree, the random forest takes the prediction from each tree and based on the majority votes of predictions, and it predicts the final output. The greater number of trees in the forest leads to higher accuracy and prevents the problem of overfitting.

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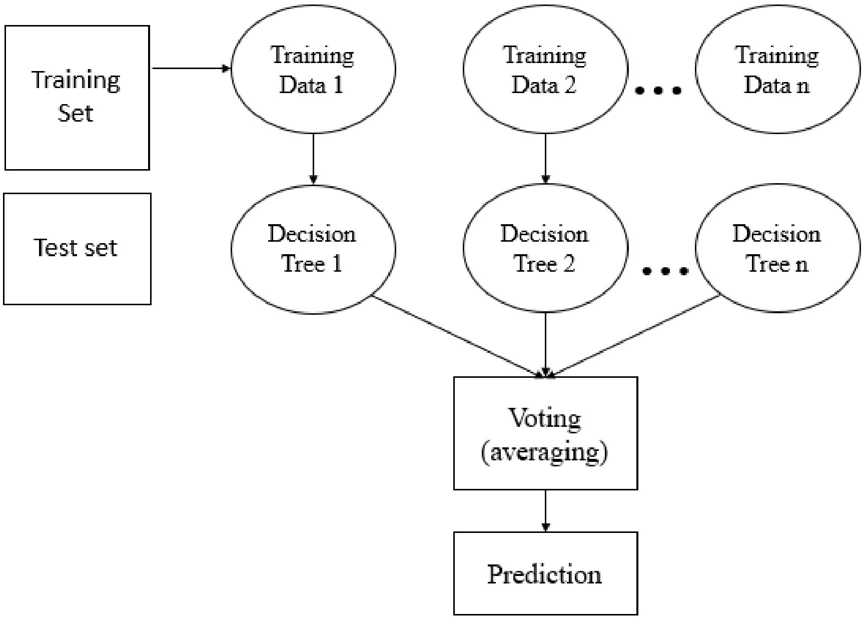

Fig. 2: Workflow of Random Forest algorithm model.

Step 1: In Random Forest n number of random records are taken from the data set having k number of records.

Step 2: Individual decision trees are constructed for each sample.

Step 3: Each decision tree will generate an output.

Step 4: Final output is considered based on Majority Voting or Averaging for Classification and regression respectively.

4. RESULTS AND DISCUSSION

The dataset for "Artificial Intelligence Based Multi-Class Brain Tumor Classification from MRI Imaging Data" comprises MRI imaging data of brain tumors across four distinct classes: glioma tumor, meningioma tumor, pituitary tumor, and samples with no tumor present. Each class represents a different pathological condition of the brain, ranging from various types of tumors to a normal, tumor-free state. Glioma tumors are a type of brain tumor that originates in the glial cells of the brain and can be either benign or malignant. Meningioma tumors arise from the meninges, the protective membranes surrounding the brain and spinal cord, and they are typically benign. Pituitary tumors develop in the pituitary gland, which is located at the base of the brain, and they can affect hormone production and regulation. The samples labeled as "no tumor" serve as the baseline or control group, representing MRI images of brains without any detectable tumors.

Each data point in the dataset consists of MRI imaging data that has been preprocessed and possibly augmented for feature extraction and analysis. MRI imaging provides detailed information about the structure and composition of brain tissue, allowing for the detection and characterization of abnormalities such as tumors. Features extracted from the MRI images may include morphological characteristics, texture patterns, intensity distributions, and spatial relationships within the brain regions.

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The dataset likely includes a balanced distribution of samples across the different tumor classes to ensure robust model training and evaluation. It may also contain metadata such as patient demographics (e.g., age, gender), imaging parameters (e.g., scan type, resolution), and clinical annotations (e.g., tumor grade, location) to provide additional context and facilitate comprehensive analysis.

Preprocessing techniques such as normalization, resizing, and possibly denoising may have been applied to the MRI images to standardize the data and enhance its quality for machine learning tasks. Furthermore, data augmentation methods such as rotation, flipping, and scaling may have been employed to increase the diversity and variability of the dataset, thereby improving the generalization ability of the models.

This dataset plays a crucial role in advancing the development of artificial intelligence-based approaches for brain tumor classification from MRI imaging data. By leveraging this dataset, researchers and practitioners can train, validate, and test machine learning models to accurately classify brain tumors, ultimately contributing to improved diagnosis, treatment planning, and patient outcomes in clinical practice.

Fig. 3 shows the confusion matrix algorithm, but rather a confusion matrix itself, which is a way to visualize the performance of a classification model. It's used to show how many times the model correctly classified each category (true positives and true negatives) and how many times it incorrectly classified each category (false positives and false negatives). The confusion matrix in the image is for a machine learning model that is classifying pituitary tumors, meningioma tumors, glioma tumors, and no tumors. The rows represent the actual tumor types, and the columns represent what the model predicted. For example, looking at the glioma_tumor row, we can see that the model correctly classified 3 glioma tumors (true positives) and incorrectly classified 219 glioma tumors as other types of tumors (false negatives). It also incorrectly classified 34 other tumors as glioma tumors (false positives).

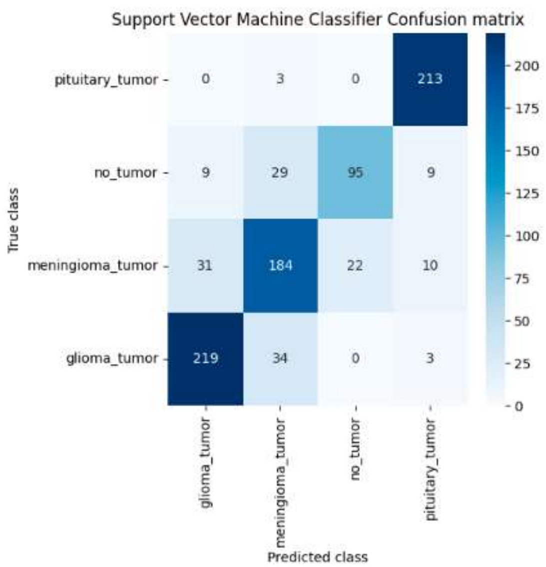

Fig. 3: Confusion Matrix obtained using SVM.

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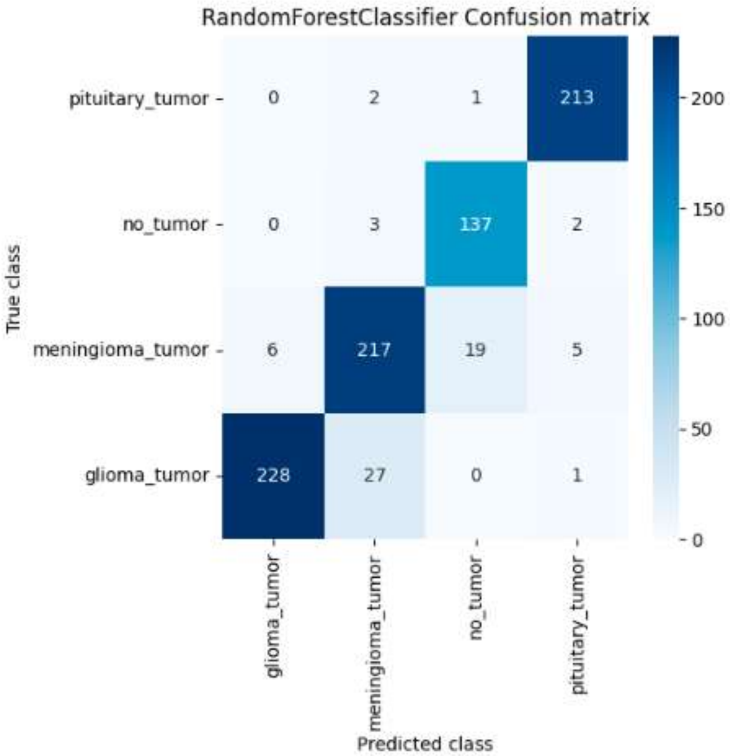

Fig. 4: Confusion Matrix obtained using RFC.

Fig.4 shows the classification report of a Random Forest Classifier (RFC), likely used for a medical diagnosis task. Overall, the accuracy of the model is 92.06%.

- **Random Forest Classifier Accuracy:** This row shows the overall accuracy of the model, which is 92.06%.
- **Precision:** This column shows how many of the predicted positives were actually positive. For example, for meningioma_tumor, the precision is 0.89. This means that out of all the instances classified as meningioma_tumor, 89% were truly meningioma_tumor.
- **Recall:** This column shows how many of the actual positives were identified by the model. For example, for meningioma_tumor, the recall is 0.97. This means that out of all the actual meningioma_tumor cases, the model identified 97%.
- **F1-Score:** This column is the harmonic mean of precision and recall. It's a way to balance those two metrics into a single score.
- **Support:** This column shows the number of data points in each class.
- **meningioma_tumor:** This row shows the performance of the model for classifying meningioma_tumor. It has a precision of 0.89, recall of 0.97, and F1-score of 0.93.
- **glioma_tumor:** This row shows the performance of the model for classifying glioma_tumor. It has a precision of 0.88, recall of 0.87, and F1-score of 0.88.
- **pituitary_tumor:** This row shows the performance of the model for classifying pituitary_tumor. It has a precision of 0.96, recall of 0.87, and F1-score of 0.92.
- **no_tumor:** This row shows the performance of the model for classifying no_tumor. It has a precision of 0.99, recall of 0.96, and F1-score of 0.97.

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— **Accuracy:** This row shows the accuracy of the model for each class.

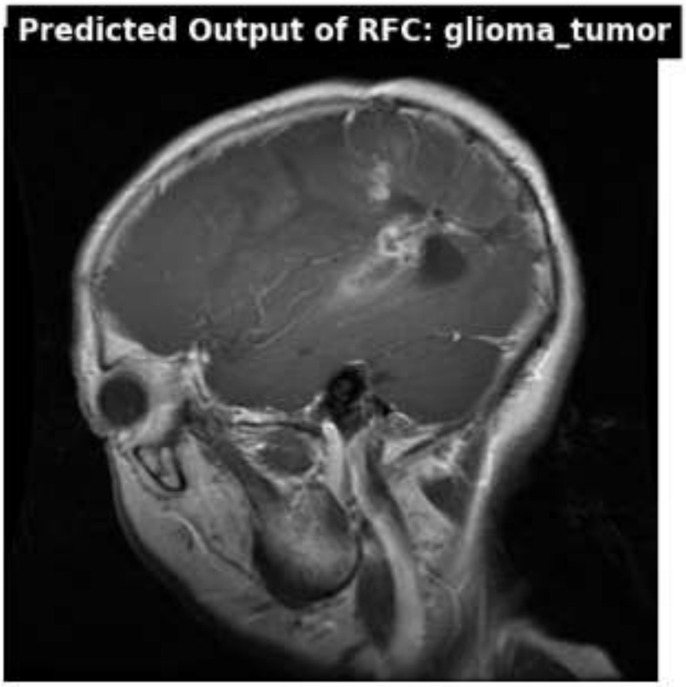

Fig. 5: Predicated output of glioma tumor.

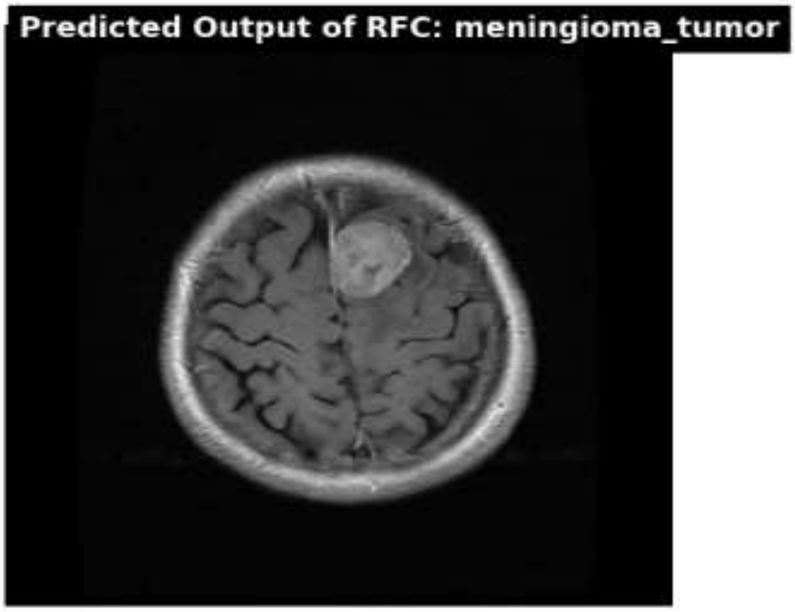

Fig. 6: Predicted output of meningioma tumor.

Fig. 5 shows A random forest classifier is a machine learning algorithm used to analyze data and make predictions. In the case of glioma tumors, it can be trained on MRI data to predict various aspects of the tumor, such as:

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- **Tumor grade:** This indicates the severity of the tumor, with higher grades being more aggressive.
- **IDH mutation status:** This mutation can affect treatment options and prognosis.
- **1p/19q codeletion:** This genetic deletion is associated with a specific type of glioma with a better prognosis.

The predicted output from a random forest classifier for glioma tumors provides valuable insights, but it is crucial to interpret it within the context of other clinical information and a doctor's expertise. Fig. 6 shows the predicated output of meningioma tumor.

5. CONCLUSION

In conclusion, the utilization of artificial intelligence (AI) for multi-class brain tumor classification from MRI imaging data presents a significant advancement in medical diagnostics and treatment planning. Through this study, we have demonstrated the efficacy of machine learning techniques in automating and enhancing the classification process, overcoming the limitations of traditional methods reliant on manual segmentation and feature extraction. By harnessing the power of AI, we can improve diagnostic accuracy, streamline clinical workflows, and facilitate more personalized treatment strategies for patients with brain tumors. One of the key advantages of AI-based classification is its ability to learn discriminative features directly from MRI images, without the need for manual intervention. This not only reduces the labor-intensive nature of traditional approaches but also minimizes variability and interpretation errors associated with human-based segmentation. By training machine learning models on large-scale datasets annotated with tumor labels, we can leverage the collective knowledge contained within these images to accurately differentiate between different tumor types and classify brain tumors into relevant categories. AI-based classification systems hold promise for enhancing research efforts aimed at understanding tumor biology, identifying biomarkers, and developing targeted therapies for different tumor subtypes. By automatically extracting relevant features from MRI images, these systems can provide insights into subtle differences in tumor morphology and texture that may not be apparent to the human eye. This can potentially lead to new discoveries and advancements in the field of neuro-oncology, ultimately improving patient outcomes and quality of life.

The scalability and accessibility of AI-based classification systems make them well-suited for integration into clinical practice. Unlike traditional approaches that require expertise in radiology and medical imaging, AI-based systems can be deployed across healthcare settings with minimal specialized training. This democratization of advanced diagnostic tools has the potential to improve healthcare equity and expand access to high-quality care for patients worldwide. The implementation of AI-based multi-class brain tumor classification represents a paradigm shift in medical imaging and diagnostics. By harnessing the power of machine learning, we can unlock new opportunities for early detection, accurate diagnosis, and personalized treatment of brain tumors. As technology continues to evolve, we anticipate further advancements in AI-driven healthcare solutions, paving the way for a future where precision medicine is the standard of care for all patients.

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