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AI IN THE MRI ERA TRANSFORMING BRAIN TUMOR DIAGNOSYICS WITH MACHINE LEARNING INNOVATIONS

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ABSTRACT: ***Brain tumors have increased significantly over the past decade, with around 700,000 new cases recorded globally each year. In the US, there were 84,000 cases in 2023, underscoring the need for better diagnostics. Ways for successfully managing and treating these illnesses. Radiologists' ability in analyzing medical imaging data, such as MRI images, is crucial for manually classifying brain tumors. These procedures are labor-intensive, time-consuming, and prone to interpretation errors, resulting in inconsistent diagnoses. Current diagnostic techniques have limitations due to subjective assessment and human error. Objective and scalable solutions are needed database The integration of Taiwan's medical resources has the basis for cross-service cooperation. Machine learning is a viable solution for automating processes and it's a promising solution for automating classification and improving diagnostic accuracy. Machine learning models trained on large picture repositories produce consistent and reliable results, allowing for faster and more accurate diagnosis. This technology development improves medical imaging and brain tumor categorization, overcoming limitations of older me These approaches may struggle to capture small changes in tumor form or texture, resulting in inaccurate classification. Furthermore, traditional approaches may necessitate knowledge in radiology and medical imaging, restricting their accessibility and scalability in clinical settings. Furthermore, human feature engineering may overlook essential tumor traits or fail to use the potential of MRI data for categorization. The suggested approach uses machine learning techniques to automate and improve brain tumor categorization from MRI imaging data, thereby overcoming the limitations of existing systems. This study uses machine learning methods to extract discriminatory information straight from MRI scans. Training models on large-scale MRI datasets annotated with tumor labels allows the proposed algorithms to successfully differentiate between different tumor types and reliably categorize brain tumors into important categories.***

KEYWORDS: Brain tumors, MRI, Machine learning, MRI datasets, Training models, Categorization, Diagnostic accuracy.

1.INTRODUCTION

The manual classification of brain cancers requires radiologists to possess the critical skill of evaluating medical imaging data, including MRI scans. These processes need a lot of work, take a long time, and are prone to interpretation errors, which can lead to inconsistent diagnoses. Subjective evaluation and human error are the main causes of the limitations in current diagnostic procedures. Database solutions that are scalable and objective are required. The foundation for cross-service collaboration is the integration of Taiwan's medical resources. Automating processes with machine learning is a feasible approach, and it holds great potential for enhancing diagnostic precision and automating classification. Large image libraries are used to train machine learning models, which yield consistent and dependable results that enable quicker and more precise diagnosis. This technological advancement overcomes the limits of the older me by improving medical imaging and brain tumor classification. These methods may not be able to accurately classify modest changes in the form or texture of the tumor. Moreover, conventional methods could require expertise in radiology and medical imaging, which would limit their use and expandability in clinical environments. Moreover, human feature engineering could miss important tumor characteristics or not fully utilize MRI data for classification. Moreover, human feature engineering could miss important tumor characteristics or not fully utilize MRI data for classification. The proposed method overcomes the shortcomings of current systems by automating and improving brain tumor classification from MRI imaging data using machine learning techniques. In this work, discriminating information is directly extracted from MRI scans using machine learning techniques. The suggested techniques can accurately classify brain cancers into significant categories and successfully distinguish between various tumor types by training models on large-scale MRI datasets labeled with tumor labels.

2. LITERATURE SURVEY

[1]. As a result, any aberration in the brain has the potential to endanger human health. The most serious of these anomalies are brain tumors. Brain tumors are uncontrolled and abnormal growths of cells in the brain that are divided into two types: primary tumors and secondary tumors. Primary tumors exist in brain tissue, whereas secondary

cancers spread from other regions of the body to the brain via the bloodstream

[2]. Glioma and meningioma are two of the most dangerous forms of brain tumors, and they can kill a patient if not detected early

[3]. In fact, glioma is the most prevalent brain tumor in humans

[4]. The World Health Organization (WHO) classifies brain tumors into four classes Grade 1 and 2 tumors are lower-level tumors (e.g., meningioma), whereas grade 3 and 4 tumors are more severe (e.g., glioma). In clinical practice, the incidence rates of meningioma, pituitary, and glioma tumors are roughly 15%, 15%, and 45%, respectively.

Treatment options for brain tumors vary depending on their location, size, and form. Surgery is currently the most common treatment for brain tumors because it has no brain-related side effects

[5] MRI is the most preferred imaging modality because it is the only non-invasive and non-ionizing method that provides useful information in 2D and 3D formats about brain tumor kind, size, shape, and position

[6]. However, due to the high volume of patients, manually evaluating these photos is time-consuming, stressful, and potentially error-prone [7]. To address this issue, an automatic computer-aided diagnosis (CAD) system is needed to reduce the strain of brain MRI categorization and diagnosis while also serving as a tool for radiologists and doctors.

Several attempts are being made to create a very accurate and resilient method for automatically classifying brain tumors. However, due to significant inter and intra form, texture, and contrast differences, it remains a difficult problem. Traditional machine learning (ML) techniques rely on handmade characteristics, limiting the robustness of the solution. Deep learning approaches, on the other hand, automatically extract meaningful information, resulting in considerably superior performance. Additionally, we created the innovative feature ensemble technique for the MRI-based brain tumor classification job in order to examine the advantages of mixing features from various pre-trained CNN models. We presented a novel feature assessment and selection procedure in which nine separate ML classifiers are used to assess the deep features from thirteen different pre-trained CNNs, and the features are chosen according to our suggested feature selection criteria. We created a synthetic feature in our suggested framework by concatenating the top three deep features from three distinct CNNs. Since different CNN architectures can capture distinct information in brain MR images, the concatenation technique combines the information from many CNNs to produce a more discriminative feature representation than using the feature retrieved from a single CNN model. In contrast to the majority of earlier efforts that used conventional feature extraction approaches, an ensemble of deep features is then fed into multiple machine learning classifiers to predict the final output

[8]. Using nine distinct machine learning classifiers and thirteen distinct pre-trained deep convolutional neural networks on three distinct datasets, we conducted a thorough evaluation in our experiment:The findings of our experiment show that the ensemble of deep characteristics can greatly enhance performance. In conclusion, the following is a list of our contributions:

We created and put into practice a fully automatic hybrid approach for classifying brain tumors that makes use of both (1) pre-trained CNN models to extract deep features from brain MR images and (2) machine learning classifiers to accurately diagnose the type of brain tumor.

We suggested a brand-new approach with three steps: To achieve state-of-the-art performance for brain tumor classification in brain MR images, (1) use pre-trained CNN models to extract deep features for better generalization and meaningful information extraction, (2) use several ML models that have been fine-tuned for our task to select the top three performing features, and (3) combine them to build the ensemble model.

We developed and implemented a completely automated hybrid technique for identifying brain cancers that uses (1) pre-trained CNN models to extract deep features from brain MR images and (2) machine learning classifiers to reliably detect the kind of brain tumor.

We proposed a brand-new technique in three steps: To achieve cutting-edge performance for brain tumor classification in brain MR images, (1) use pre-trained CNN models to extract deep features for better generalization and meaningful information extraction, (2) select the top three performing features from several ML models fine-tuned for our task, and (3) combine them to build the ensemble model.

Traditional ML methods include pre-processing, feature extraction, reduction, and classification. Traditional machine-learning approaches rely heavily on feature extraction to improve classification accuracy. There are two primary forms of feature extraction. The first type of feature extraction involves low-level (global) features like texture and intensity, as well as first-order statistics like mean, standard deviation, and skewness. Second-order statistics include gray-level co-occurrence matrix (GLCM), wavelet transform (WT), Gabor features, and shape. Selvaraj et al.

[9]. We used first- and second-order statistics with least square support vector machine (SVM) to create a binary classifier for identifying normal and pathological brain MR images. John et al and others. The conventional ML approaches consist of numerous

[10] employed GLCM and discrete wavelet transformation technologies to identify and classify tumors. The low-level features efficiently depict the image; nevertheless, their representation capacity is restricted because most brain tumors have similar appearances, such as texture, border, form, and size. Ullah et al.

3. PROPOSED METHODOLOGY

The study sets out to revolutionize brain tumor categorization using magnetic resonance imaging (MRI) data, acknowledging its critical importance in clinical practice. Accurate tumor classification allows doctors to better record optimal treatment options, monitor disease trajectories, and evaluate treatment efficacy. Using the power of machine learning, this project seeks to provide radiologists with tools that supplement their experience, reducing interpretation errors and improving diagnosis accuracy. Beyond the clinic, brain tumor classification is critical for expanding our understanding of tumor biology, identifying biomarkers, and developing targeted therapeutics for various tumor subtypes.

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 address these issues, the study proposes a paradigm shift via the use of machine learning techniques. The proposed technique aims to automate and improve brain tumor classification by using machine learning models to extract discriminative characteristics directly from MRI images. Based on the richness of large-scale MRI datasets annotated with tumor labels, these algorithms are prepared to distinguish between distinct tumor types and categorize brain cancers with exceptional precision.

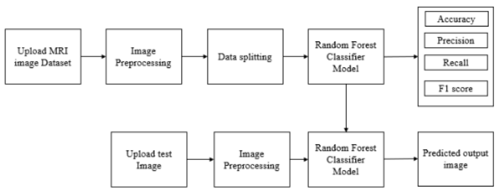

Figure 1: Block Diagram.

4. EXPERIMENTAL ANALYSIS

For research, diagnosis, and therapy planning, an accurate classification of brain tumors from MRI data is essential. Conventional techniques take a lot of time and are prone to mistakes. Understanding tumor biology can be aided by machine learning models, which can increase accuracy and decrease errors.

SVM and RFC are used in this work to classify brain tumors. Using a polynomial kernel, SVM can handle complex data more effectively. RFC is appropriate for this task due to its scalability and resilience.

We will use machine learning approaches, notably Support Vector Machine (SVM) and Random Forest Classifier (RFC), to construct multi-class brain tumor classification from MRI imaging data..

For the further classification part,import the required libraries: Bring in the necessary modules for evaluation, visualization, machine learning, and data manipulation.

Preprocess and load data: After the dataset has been pre-processed, load it and divide it into features and labels.

Save and train the SVM model: If an SVM model has already been trained, load it; if not, use the training data to train a new SVM model and save it for later use.

Make forecasts and assess SVM: Calculate performance metrics and predict tumor kinds using the test data using the trained SVM model.

Save and train the RFC model: For the Random Forest Classifier, repeat steps three and four.

• **Support Vector Machine Classifier Accuracy:** The model's total accuracy, 81.39%, is displayed in this row.

• **Precision:** The number of anticipated positives that were actually positive is displayed in this column. Meningioma tumor, for instance, has a precision of 0.86. This indicates that 86% of the cases that were diagnosed as meningioma tumor were actually meningioma tumor.

• **Recall:** The number of real positives that the model detected is displayed in this column. Meningioma tumor, for instance, has a recall of 0.85

• **F1-Score:** The harmonic mean of recall and precision is shown in this column. It's a method of combining the two measurements into one score.

• **Support:** The number of data points in each class is displayed in this column.

• **meningiomata:** This row displays the model's classification performance for meningiomata. Its F1-score is 0.85, recall is 0.85, and precision is 0.86.

The model's performance in categorizing gliomata is displayed in this row. It has a 0.74 F1-score, 0.74 precision, and 0.74 recall.

• **pituitary tumor:** The model's classification performance for pituitary tumor is displayed in this row. Its F1-score is 0.73, its precision is 0.67, and its recall is 0.81.

• **non tumor:** This row displays the model's classification performance for nontumor. Its F1-score is 0.94, its precision is 0.99, and its recall is 0.91.

• **Accuracy:** The model's accuracy for each class is displayed in this row.

• **Macro Average:** The precision, recall, and F1-score averages for each class are displayed in this row.

• **Weighted Average:** This row displays the precision, recall, and F1-score weighted by each class's support.

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```
Model loaded successfully.
Support Vector Machine Classifier Accuracy    : 82.57839721254355
Support Vector Machine Classifier Precision   : 82.49771590622655
Support Vector Machine Classifier Recall      : 81.38833042183035
Support Vector Machine Classifier FSCORE      : 81.72716134785018

 Support Vector Machine Classifier classification report
                  precision    recall  f1-score   support

     glioma_tumor       0.86      0.85      0.85       259
 meningioma_tumor       0.74      0.74      0.74       250
         no_tumor       0.67      0.81      0.73       117
  pituitary_tumor       0.99      0.91      0.94       235

         accuracy                           0.83       861
        macro avg       0.81      0.82      0.82       861
     weighted avg       0.83      0.83      0.83       861
```

Figure 2: Classification Report of SVM

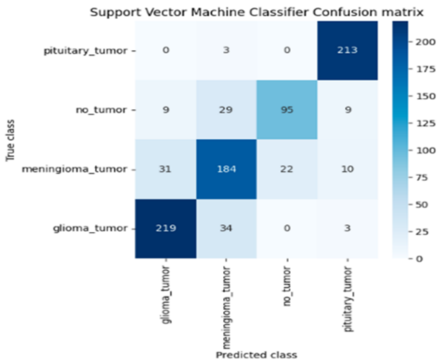

Figure 3: Confusion Matrix of SVM

The classification report of a Random Forest Classifier (RFC), most often utilized for a medical diagnosis task, is displayed in Figure 4. The model's overall accuracy is 92.06%.

Figure 5 illustrates A machine learning algorithm for data analysis and prediction is called a random forest classifier. It may be trained using MRI data to forecast many aspects of glioma tumour's, including:

A random forest classifier's predicted output for glioma tumors offers insightful information, but it's important to evaluate it in light of additional clinical data and a physician's experience.

The predicted production of a meningioma tumor is displayed in below figures.

```
RandomForestClassifier Accuracy    : 92.33449477351915
RandomForestClassifier Precision   : 92.05643220199008
RandomForestClassifier Recall      : 93.00168384067337
RandomForestClassifier FSCORE      : 92.42071450125553

 RandomForestClassifier classification report
                  precision    recall  f1-score   support

     glioma_tumor       0.89      0.97      0.93       234
 meningioma_tumor       0.88      0.87      0.88       249
         no_tumor       0.96      0.87      0.92       157
  pituitary_tumor       0.99      0.96      0.97       221

         accuracy                           0.92       861
        macro avg       0.93      0.92      0.92       861
     weighted avg       0.93      0.92      0.92       861
```

Figure 4 Classification Report of RFC

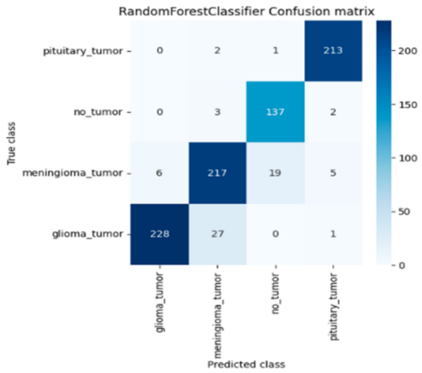

Figure 5: Confusion Matrix of RFC

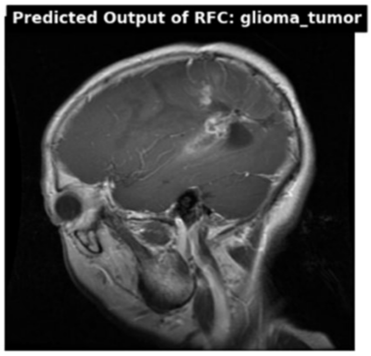

Figure 6: predicated output of glioma tumor

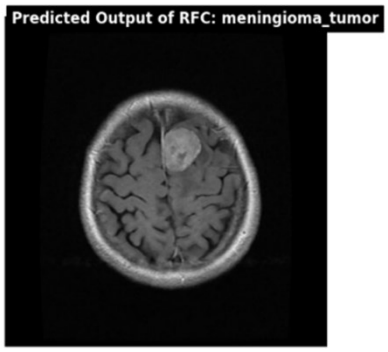

Figure 7: predicated output of meningioma tumor

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.

The ability of AI-based classification to automatically extract discriminative characteristics from MRI images without the need for human interaction is one of its main benefits. This lessens the variability and interpretation errors connected with human-based segmentation, in addition to the labour-intensive aspect of conventional methods. We may use the collective knowledge included in these photos to effectively distinguish between various tumor kinds and categorize brain tumors into pertinent groups by training machine learning models on extensive datasets labelled with tumor labels. Research efforts to comprehend tumor biology, find biomarkers, and create tailored treatments for various tumor subtypes could be improved by AI-based classification systems. These technologies can reveal small variations in tumor form and texture that might not be visible to the human eye by automatically extracting pertinent data from MRI images. This may result in fresh insights and developments in the field of neuro-oncology, which would eventually enhance patient outcomes and quality of life.

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