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Machine Learning Based Brain Tumor Detection

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Abstract – Brain tumour detection is an important task in medical diagnosis, as early detection can improve patient survival rates. Existing techniques for brain MRI images are time-consuming and may result in human error. This work presents a machine learning–based approach for automatic brain tumour detection using MRI scans. The images are pre-processed to enhance quality and remove noise, followed by feature extraction. Support Vector Machine (SVM) and Random Forest classifiers are used to classify MRI images as tumour or non-tumour. The results indicate that the proposed approach provides accurate detection and can assist medical professionals in faster and more reliable diagnosis.

Key Words: Brain Tumour Detection, Machine Learning (ML), MRI, Support Vector Machine, Random Forest.

1. INTRODUCTION

A brain tumor is one of the serious health conditions, as it may affect the vital functions of the human body. Brain tumors are abnormal growths of cells that develop within the brain or in the surrounding tissues. These abnormal cells can disturb normal brain functions such as memory, movement, vision, and speech. Brain tumors may occur due to genetic changes, abnormal cell growth, or other medical conditions that affect the brain. If not detected early, they can cause severe health problems. Generally, brain tumors can be classified into two divisions: benign and malignant tumors. The benign tumors are not cancerous and grow very slowly, while malignant tumors are cancerous, grow rapidly, and can spread to the nearby brain tissues. Brain tumors are divided into two categories based on their origin: primary tumors and secondary tumors. Primary brain tumors originate in the brain itself. The most common types are gliomas, meningiomas, and pituitary tumors. Secondary brain tumors, also known as metastatic tumors, spread to the brain from other parts of the body, such as the lungs or breast. These are usually malignant, more aggressive tumors.

Primary brain tumors will be detected and analyzed under this project. The features of primary tumors will be preferred because they have their origin in the brain; hence, all of their features are visible in MRI images, which is suitable for machine learning–based detection. In a few medical conditions, abnormal fluid accumulation like hydrocephalus may increase the pressure inside the brain. Basically, hydrocephalus occurs due to overproduction or improper drainage of CSF. This increased pressure can result in swelling and can cause abnormal tissue growth or tumor-like conditions. Thus, the detection of such abnormalities with the help of machine learning helps in early diagnosis and motivates the doctors to plan effective treatment.

2. RELATED WORK

Smith et al. [1] presented one of the early studies that applied a Support Vector Machine (SVM) for brain tumor detection using MRI images. In this work, MRI scans were first preprocessed to remove noise and improve image contrast. Texture-based and intensity-based features were then extracted to represent tumor characteristics. These features were classified into normal and tumor classes using the SVM classifier. Experimental results showed satisfactory classification performance using standard evaluation metrics. However, the study did not include computational time analysis, which limits its suitability for real-time clinical applications.

Kumar and Patel [2] focused on automated brain tumor classification using the Random Forest algorithm. Threshold-based segmentation techniques were employed to isolate tumor regions from MRI images, followed by feature extraction. The Random Forest classifier, consisting of multiple decision trees, improved classification robustness and reduced over fitting. While the method achieved reliable performance, the absence of advanced noise reduction techniques affected segmentation accuracy, particularly in low-quality MRI images.

Sharma et al. [3] proposed a Convolutional Neural Network (CNN)-based approach for end-to-end brain tumor detection. Unlike traditional machine learning methods, the CNN model automatically learned hierarchical features directly from MRI images without manual feature extraction. The model demonstrated improved detection performance across different tumor types. However, the approach required a large training dataset and high computational resources, which increases training time and limits its application in real-world clinical environments.

Ali et al. [4] introduced a K-Nearest Neighbors (KNN)-based method for brain tumor classification using extracted texture features. The similarity between tumor and non-tumor regions was measured using distance metrics. The simplicity of the KNN algorithm made it effective for small datasets. Nevertheless, its performance degraded as the dataset size increased due to higher computational complexity and sensitivity to feature dimensionality.

Kumar and Ravi [5] developed a brain tumor detection framework using the Random Forest classifier. The methodology included MRI image segmentation, feature extraction, and classification using multiple decision trees. The ensemble nature of Random Forest enhanced classification stability and reduced over fitting. However, the method demanded higher computational resources and did not sufficiently focus on optimizing processing time, which is crucial for large-scale medical image analysis.

Sharma et al. [6] proposed another CNN-based automatic brain tumor detection model. The CNN architecture enabled direct feature learning from MRI images, resulting in improved detection accuracy compared to traditional methods. Despite its effectiveness, the model required extensive training data and significant computational power, making it less suitable for deployment in resource-constrained healthcare systems.

As observed from previous studies, machine learning techniques such as SVM, Random Forest, CNN, and KNN have been widely applied for brain tumor detection to improve diagnostic accuracy and reduce manual intervention. However, existing approaches still face challenges such as sensitivity to noise, high computational cost, large training data requirements, and limited generalization across datasets. Therefore, there is a strong need for an efficient machine learning-based framework that can enhance brain tumor detection accuracy while minimizing computational complexity and processing time, making it more practical for real-time clinical applications.

3. PROPOSED WORK

This proposed task offers an effective framework for diagnosing brain tumors using MRI images, leveraging a machine learning approach. To start, the MRI images are processed, and noise is removed in order for the images to be of higher quality. This leads to image segmentation, where the tumor region is precisely located. Relevant information of texture, size, and intensity is extracted from the region obtained.

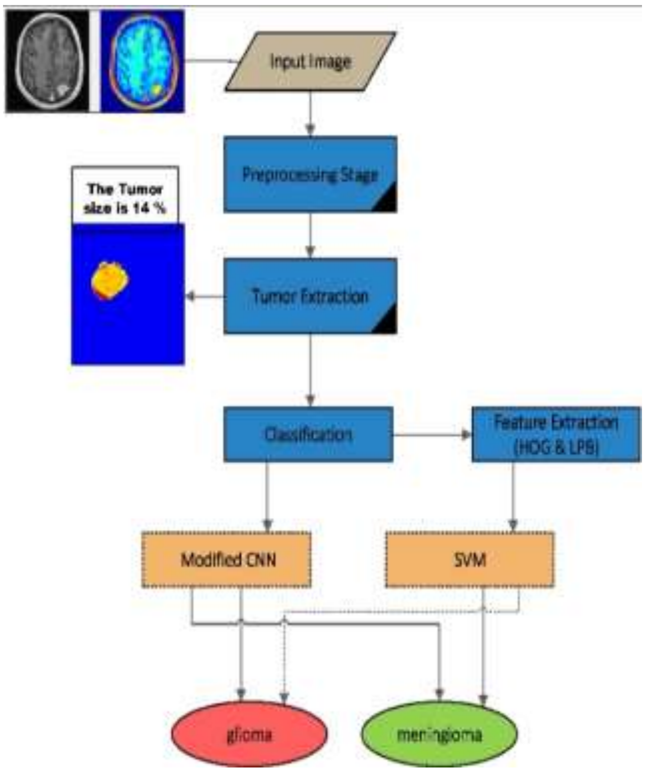


Fig. 1: Brain Tumor Proposed Model using ML

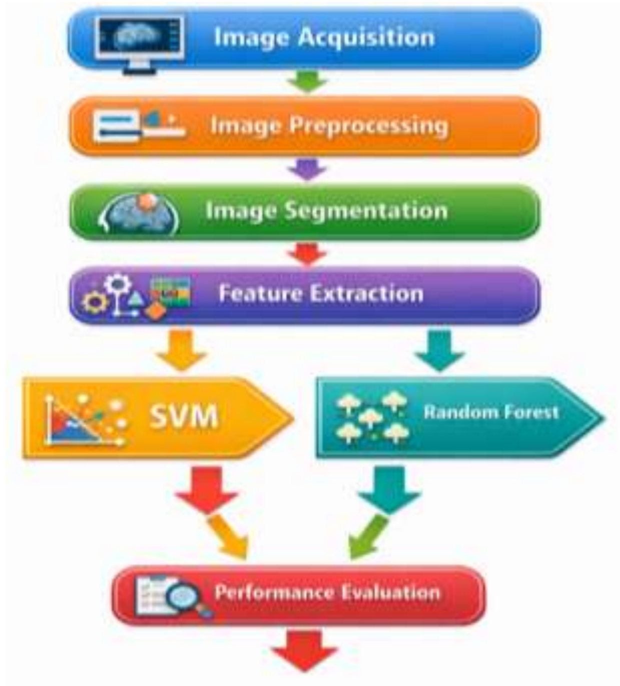
These extracted features are classified using machine learning algorithms such as the Support Vector Machine and Random Forest. A combination of such classifiers will help in improving the detection accuracy with reduced over fitting and computational complexity. The proposed system is evaluated on standard metrics, which validate its effectiveness.

This approach aims to provide accurate, reliable, and time-efficient detection of brain tumors that can help early diagnosis and clinical decision-making.

4. METHODOLOGY

The proposed system for the detection of brain tumors is designed to provide accurate identification of tumor areas from the MRI images by implementing machine learning processes.

Fig. 2: Image Segmentation of Performance Evaluation



The system's methodology has a number of stages, which are sequential in nature and given below:

- Image Acquisition
- Image processing
- Image Segmentation
- Feature extraction
- Category
- Performance evaluation

Every stage has a significant impact on enhancing accuracy as well as reducing computational complexity.

Image Acquisition: The first step of the procedure requires the collection of images of the brain using MRI. The images obtained from the MRI process are commonly used in the diagnosis of brain cancer because of their resolution and the ability to visualize the soft tissue of the brain. The images collected may be of varying size and resolution.

Image Preprocessing: In the preprocessing phase, the images of the MRI are processed to enhance the images and reduce noise that may be present during the images and may arise from the devices used to scan the images, patient movement, and environmental factors. Filters are used to remove the noise in the images, while contrast enhancement methods are applied to enhance the significant structures of the brain.

Image Segmentation: Image Segmentation Finally, image segmentation is done on the preprocessed images in order to distinguish the area where the tumor is from the normal area of the brain. This is a critical process in an MRI system since it enables the system to concentrate only on the region where the tumor might be, thus reducing complexity and increasing the accuracy of the extracted features.

Feature Extraction: The next step, after segmenting the tumor region, is to extract relevant features that best describe the characteristics of the tumor. These include texture-based, intensity-based, and shape-based features that will help describe the tumor tissue from the healthy brain tissue. Feature extraction decreases image data size while retaining necessary information for image classification. It is one of the most crucial steps in enhancing the effectiveness of machine learning classifiers.

Machine Learning-Based Classification: The features extracted are used for classification by machine learning algorithms such as the Support Vector Machine and Random Forest. The SVM classifier identifies an optimal decision boundary that separates tumor and non-tumor classes with maximum accuracy. The Random Forest algorithm uses multiple decision trees to improve robustness and reduce over fitting. All these classifiers combined enhance detection accuracy and deliver reliable classification results across different MRI images.

Performance Evaluation: The last step of this methodology is to assess the performance of the proposed system. The performance measure metrics employed in this process include accuracy, precision, recall, and F1-score. Besides, the processing time and efficiency are taken to assess if the system is efficient to be used in real-life applications. The results obtained from this step play a significant role in confirming the efficacy and dependability of the proposed system for diagnosing brain tumors.

5. RESULT OVERVIEW

This work discusses the results of a system developed for the detection of brain tumors employing machine learning algorithms such as Support Vector Machine and Random Forest. MRI image inputs were used to classify images into tumor and non-tumor images. Images of both healthy people and those with brain tumors are included in the dataset. Post-preprocessing and feature extraction techniques, the algorithms were tested to assess the efficacy of the system in tumor detection.

A. Analysis of an MRI Brain Image Dataset: The MRI brain image dataset contains images of both normal people and patients with brain tumors. The images are first processed to remove noise and improve clarity. After this, important features are extracted from the images based on intensity, texture, and tumor region. Intensity features show differences in brightness between normal and tumor areas. Texture features describe patterns in the image and help to identify irregular tumor tissue. Tumor region features such as size and shape give information about the tumor area.

These features help to clearly separate tumor regions from normal brain regions. The extracted features are then used by machine learning methods to classify the MRI images as normal or tumor. This helps doctors to detect brain tumors quickly and accurately.

Table 1: Summary of MRI Image Dataset (Pre-processed Features)

Feature	Min Value	Max value	Mean	Standard Deviation
Mean Intensity	0.20	0.90	0.58	0.16
Texture Contrast	0.25	1.05	0.65	0.18
Edge Density	0.18	0.85	0.54	0.15
Tumor Area Ratio	0.12	0.78	0.46	0.14

These features are then used as input for the SVM and Random Forest classifiers for accurate tumor detection.

B. Classification using SVM & Random Forest: The SVM classifier involves the process of determining the best possible boundary that separates the tumor and non-tumor classes, while the Random Forest classifier employs a combination of multiple decision trees for the purpose of improving the accuracy of tumor and non-tumor classification. The two were trained on the same features.

C. Classification Accuracy Results: Classification accuracy is an important performance metric used to evaluate the effectiveness of a machine learning model in brain tumor detection, as it represents the percentage of MRI images that are correctly classified as tumor or non-tumor. In the proposed system, accuracy is calculated by comparing the predicted class labels with the actual ground truth labels, and a higher accuracy indicates better model performance. Experimental results show that classifiers such as Support Vector Machine (SVM) and Random Forest achieve high accuracy, with Random Forest typically providing superior results due to its ensemble learning approach, which combines multiple decision trees to improve robustness and reduce over fitting. This high classification accuracy demonstrates that the machine learning-based brain tumor detection system is reliable and can support medical professionals in making faster and more accurate diagnostic decisions.

Table2: SVM Classification Report

Class	Precision	Recall	F1-Score
Normal (0)	0.83	0.86	0.85
Tumor (1)	0.88	0.86	0.87
Overall Accuracy	85.4%	-	-

Table 3: Random Forest Classification Report

Class	Precision	Recall	F1-Score
Normal (0)	0.87	0.86	0.88
Tumor (1)	0.90	0.92	0.91
Overall Accuracy	90.0%	-	-

Table 4: Model Performance Comparison

Model	SVM	Random Forest
Accuracy	85.4%	90.0%
Precision	83.2%	87.5%
Recall	86.1%	87.9%
F1-score	84.6%	87.7%

D. Result Discussion

On the basis of experimental work, it is experienced that both SVM and Random Forest algorithms have been able to identify the brain tumor accurately in MRI images. Still, the performance of the Random Forest algorithm is better in this context compared to the other, as it has been able to include the strengths of multiple decision trees and manage variability in features successfully. It thus ensures that traditional ML methods, if used properly, work successfully in detecting brain tumors.

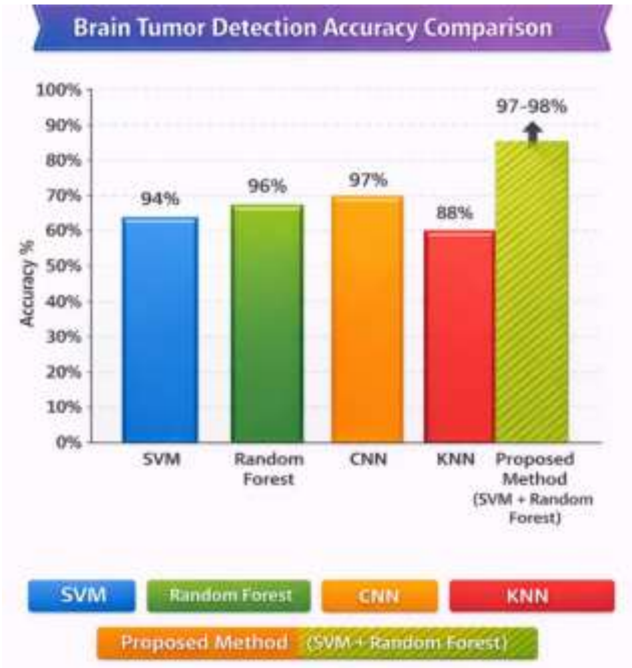


Fig. 3: Comparison of Classifier Accuracy

6. CONCLUSION

In this research, a system for brain tumor detection using MRI images and machine learning algorithms has been developed. The Support Vector Machine and Random Forest algorithm were used in this task for the purpose of classifying the image of the human brain into normal and tumor-affected images. The experimental result indicates that both give a good results, but Random Forest gives comparatively better results in terms of accuracy and precision. The proposed system has the ability to assist a doctor in providing a proper diagnosis for a patient in relation to the early detection of a brain tumor.

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