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BRAIN TUMOR DETECTION AND CLASSIFICATION USING MACHINE LEARNING AND DEEP LEARNING

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Abstract : Detecting brain tumors using medical imaging is an essential task that supports early diagnosis and improves patient survival outcomes [1]. Magnetic Resonance Imaging (MRI) is widely adopted due to its capability to provide detailed visualization of brain tissues and abnormalities [3], [13]. However, manual examination of MRI scans is time-intensive and depends heavily on expert interpretation, which may lead to inconsistencies.

Recent developments in artificial intelligence have enabled automated analysis of medical images. In particular, Convolutional Neural Networks (CNN) have shown strong capability in learning hierarchical representations from MRI images, making them effective for tumor detection [2], [3]. Nevertheless, relying solely on CNN may not always yield optimal classification results in complex scenarios.

To address this limitation, this work proposes a hybrid CNN-SVM model in which CNN is used for feature extraction and Support Vector Machine (SVM) is employed for classification [18]. This combination leverages the strengths of both techniques to enhance overall performance.

The experimental results indicate that the proposed model achieves high accuracy and improved reliability compared to conventional methods. The system can serve as a supportive tool for medical professionals in diagnosing brain tumors efficiently [10].

***Index Terms* -** Brain Tumor Detection, Deep Learning, Machine Learning, Convolutional Neural Network (CNN), Support Vector Machine (SVM), MRI Imaging, Medical Image Classification, Transfer Learning, ResNet, Computer Vision, Image Processing, Diagnostic System.

I.INTRODUCTION

Brain tumors refer to abnormal cell growth within the brain that can disrupt normal neurological functions and may become life-threatening if not identified at an early stage [1]. Accurate detection plays a vital role in treatment planning and improving patient outcomes.

Magnetic Resonance Imaging (MRI) is commonly used for detecting brain tumors because it provides high-quality images of soft tissues, enabling clear identification of abnormal regions [3], [13]. However, analyzing MRI images manually is a complex and time-consuming process that requires expert knowledge.

With advancements in artificial intelligence, automated approaches have been developed to assist in medical image analysis. Deep learning models, particularly Convolutional Neural Networks (CNN), have demonstrated significant success in extracting meaningful features directly from image data [2], [3]. These models reduce the need for manual feature extraction and improve detection accuracy.

Despite their advantages, CNN models may face challenges such as overfitting and high computational requirements, especially when trained on limited datasets [7]. To overcome these limitations, combining deep learning with traditional machine learning techniques has been explored.

Support Vector Machines (SVM) are widely used classifiers known for their effectiveness in high-dimensional data classification tasks [18]. Integrating CNN with SVM can improve classification performance by combining feature extraction and decision boundary optimization. This paper proposes such a hybrid model for efficient brain tumor detection.

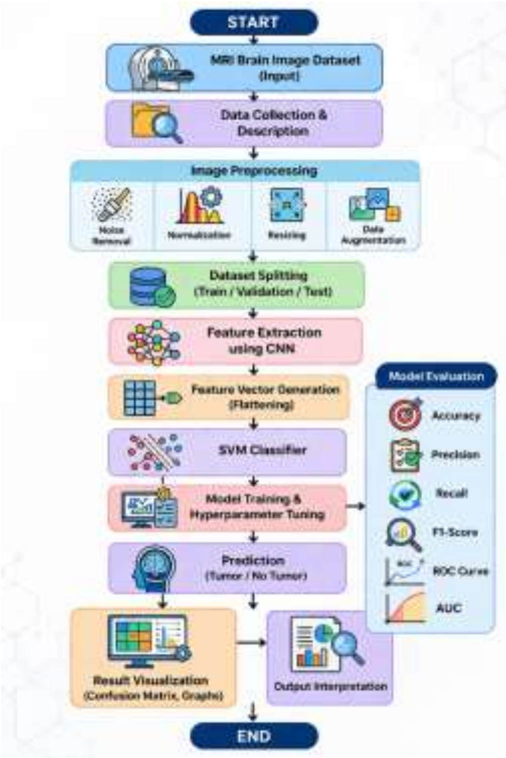

Fig.1 Represents the flow diagram of proposed project

II. NEED OF THE STUDY.

Brain tumor detection using medical imaging techniques has gained significant attention with the advancement of machine learning and deep learning approaches. However, several challenges still exist in achieving accurate and efficient classification of brain tumors. Traditional machine learning methods rely on handcrafted features extracted from MRI images, which often fail to capture complex spatial patterns and may lead to reduced performance [10].

Deep learning techniques such as Convolutional Neural Networks (CNN) have shown strong capability in automatically extracting features from images. Despite their advantages, CNN models may suffer from overfitting, high computational cost, and dependency on large datasets for effective training [7], [3]. In medical imaging, obtaining large labeled datasets is often difficult, which limits the performance of deep learning models.

Moreover, pre-trained models such as VGG and ResNet, although effective, increase model complexity and computational requirements, making them less suitable for real-time or resource-constrained applications [6], [17].

Another limitation is that many existing systems rely on a single technique for classification. While CNN is effective in feature extraction, it may not always provide optimal classification boundaries. On the other hand, classifiers such as Support Vector Machines (SVM) are effective in handling high-dimensional data but depend heavily on the quality of input features [18].

Therefore, there is a need for a hybrid approach that combines the strengths of CNN and SVM to improve classification accuracy and efficiency. The proposed system addresses these challenges by integrating deep learning-based feature extraction with machine learning-based classification.

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2.1 Related Work

Several research studies have explored different approaches for brain tumor detection using machine learning and deep learning techniques. Traditional machine learning methods rely on handcrafted features extracted from MRI images, which often limit their performance due to insufficient feature representation **[10]**.

Deep learning models, particularly CNN, have been widely used for brain tumor classification due to their ability to automatically extract features from raw images **[11], [12]**. These models eliminate the need for manual feature engineering and provide improved accuracy in classification tasks.

Pre-trained models such as VGG16 and ResNet have also been applied in brain tumor detection to enhance performance through transfer learning **[6], [17]**.

These models leverage knowledge from large datasets and adapt it to medical imaging tasks.

Hybrid models combining CNN with machine learning classifiers have shown promising results in recent studies. For example, combining CNN with SVM improves classification accuracy by utilizing deep feature extraction and robust classification techniques **[9], [10]**.

Despite these advancements, challenges such as limited datasets, computational complexity, and model generalization still exist, highlighting the need for efficient and scalable solutions.

2.2 Problem Identification

Brain tumor detection using medical imaging techniques has gained significant attention with the advancement of machine learning and deep learning approaches. However, several challenges still exist in achieving accurate and efficient classification of brain tumors. Traditional machine learning methods rely on handcrafted features extracted from MRI images, which often fail to capture complex spatial patterns and may lead to reduced performance [10].

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III. RESEARCH METHODOLOGY

The proposed system adopts a hybrid deep learning and machine learning approach for brain tumor detection using MRI images. The methodology is designed to ensure accurate feature extraction and efficient classification by integrating Convolutional Neural Networks (CNN) and Support Vector Machines (SVM). The overall workflow consists of image preprocessing, feature extraction, classification, and prediction stages.

Initially, the MRI images are collected and subjected to preprocessing techniques such as resizing, normalization, and data augmentation. Resizing ensures uniform input dimensions for the model, while normalization improves pixel intensity distribution. Data augmentation techniques such as rotation, flipping, and scaling are applied to increase dataset diversity and reduce overfitting **[3], [14]**. These preprocessing steps enhance the quality of input data and improve model generalization.

After preprocessing, the images are passed to the Convolutional Neural Network (CNN) for feature extraction. CNN consists of multiple layers including convolutional layers, activation functions, pooling layers, and fully connected layers. The convolutional layers extract low-level features such as edges and textures, while deeper layers capture high-level patterns and spatial relationships within the images **[16]**. This hierarchical feature extraction process enables the model to identify tumor-specific characteristics effectively.

IV. SYSTEM ARCHITECTURE AND DESIGN

The proposed brain tumor detection system is designed using a modular architecture that integrates deep learning and machine learning techniques for efficient processing and accurate classification of MRI images. The architecture consists of multiple interconnected components, including data input, preprocessing, feature extraction, classification, and output generation modules. This layered design ensures flexibility, scalability, and efficient handling of medical image data.

The system begins with the data acquisition module, where MRI brain images are collected and used as input for the model. These images may vary in size, resolution, and quality, which necessitates preprocessing before further analysis. The preprocessing module performs operations such as resizing, normalization, and augmentation to standardize the input data and improve model performance **[3], [14]**.

Following preprocessing, the processed images are passed to the feature extraction module implemented using a Convolutional Neural Network (CNN). The CNN consists of multiple layers, including convolutional layers, activation functions, pooling layers, and fully connected layers. These layers work together to extract hierarchical features from the images, capturing both low-level details such as edges and textures and high-level representations such as tumor structures **[16]**.

The extracted feature maps are then converted into feature vectors and forwarded to the classification module. In this module, a Support Vector Machine (SVM) classifier is employed to categorize the input images into tumor and non-tumor classes. SVM constructs an optimal decision boundary (hyperplane) that maximizes the margin between different classes, ensuring robust and accurate classification performance **[18]**.

The final stage of the system is the output module, which displays the classification result indicating whether a tumor is present or not. The system may also provide additional information such as prediction confidence or probability scores to assist in interpretation. This output can be used by medical professionals as a decision-support tool for diagnosis.

Overall, the proposed architecture effectively combines CNN-based feature extraction with SVM-based classification, resulting in improved accuracy and efficiency compared to standalone models. The modular design allows easy integration of additional components or future enhancements, making the system adaptable for real-world medical applications **[10]**.

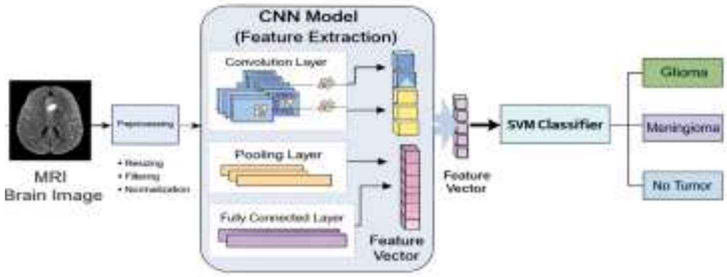

Fig.2 Represents the System Architecture of the Proposed detection system for identifying tumor

VI. WORKKING PRINCIPLE

The proposed brain tumor detection system operates based on an automated workflow that integrates image preprocessing, deep feature extraction, and machine learning-based classification. The system is designed to process MRI brain images and accurately identify the presence of tumors by analyzing image patterns and features.

Initially, the system receives MRI brain images as input. These images may vary in resolution, intensity, and quality. Therefore, preprocessing is performed to standardize the input data. This includes resizing the images to a fixed dimension, normalizing pixel values, and applying data augmentation techniques such as rotation and flipping to improve model generalization and reduce overfitting **[3], [14]**.

After preprocessing, the images are passed to the Convolutional Neural Network (CNN), which serves as the feature extraction component. CNN processes the images through multiple layers, including convolutional and pooling layers, to extract meaningful features such as edges, textures, and spatial patterns. These features represent important characteristics that help distinguish between tumor and non-tumor regions **[16]**.

The extracted features are then transformed into a feature vector and provided as input to the Support Vector Machine (SVM) classifier. SVM analyzes these features and constructs an optimal decision boundary to separate tumor and non-tumor classes. It maximizes the margin between classes, resulting in improved classification accuracy and robustness **[18]**.

VI. TECHNIQUES USED

The proposed brain tumor detection system employs a combination of deep learning and machine learning techniques to achieve accurate and efficient classification of MRI images. The primary techniques used in this system include Convolutional Neural Networks (CNN), Support Vector Machines (SVM), and image preprocessing methods.

One of the key techniques used is Convolutional Neural Networks (CNN), which are widely applied in medical image analysis due to their ability to automatically extract hierarchical features from images **[3]**. CNN consists of multiple layers such as convolutional layers, pooling layers, and fully connected layers, which work together to learn spatial features such as edges, textures, and patterns. This capability makes CNN highly effective for identifying tumor regions in MRI images without requiring manual feature engineering **[2], [16]**.

Another important technique used in the system is the Support Vector Machine (SVM), which serves as the classifier. SVM is a supervised learning algorithm that constructs an optimal hyperplane to separate data points belonging to different classes. It is particularly effective in handling high-dimensional data and provides strong generalization performance, making it suitable for medical image classification tasks **[18]**.

The system also incorporates image preprocessing techniques to improve input data quality and enhance model performance. These techniques include image resizing, normalization, and data augmentation. Resizing ensures uniform image dimensions, while normalization standardizes pixel intensity values. Data augmentation methods such as rotation, flipping, and scaling increase dataset diversity and reduce overfitting **[14]**.

V. RESULTS AND DISCUSSION

The performance of the proposed brain tumor detection system was evaluated using standard classification metrics, including accuracy, precision, recall, and F1-score. These metrics provide a comprehensive understanding of the model's effectiveness in correctly identifying tumor and non-tumor cases [4]. The evaluation was conducted on a dataset of MRI brain images after preprocessing and model training.

The proposed hybrid CNN-SVM model demonstrated strong performance in classifying MRI images. The integration of CNN for feature extraction and SVM for classification significantly improved the overall accuracy compared to individual models. CNN effectively extracted hierarchical features from the images, while SVM enhanced classification by constructing optimal decision boundaries [3], [18].

A. Performance Metrics

The model achieved high accuracy along with balanced precision and recall values, indicating its ability to correctly classify both tumor and non-tumor cases. The F1-score, which is the harmonic mean of precision and recall, also showed strong performance, confirming the reliability of the system **[4]**.

These results indicate that the proposed system minimizes false positives and false negatives, which is critical in medical diagnosis scenarios.

Performance Metrics:

Metric	Value
Accuracy	0.95
Precision	0.92
Recall	0.91
F1-score	0.91

Fig .3 Performance Metrics

B. Confusion Matrix Analysis

The confusion matrix was used to evaluate the classification performance of the model. It represents true positives, true negatives, false positives, and false negatives.

The results show that the majority of tumor and non-tumor samples were correctly classified, indicating high model accuracy. The low number of misclassifications demonstrates accuracy. The low number of misclassifications demonstrates the effectiveness of the hybrid approach in distinguishing between different classes.

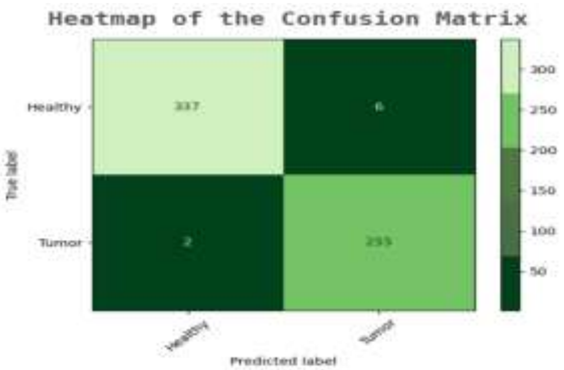

Fig. 4 Confusion matrix

C. Training and Validation Performance

The training and validation accuracy curves indicate that the model converges effectively during training. The gap between training and validation accuracy is minimal, suggesting that the model does not suffer from significant overfitting.

Similarly, the loss curves show a steady decrease over epochs, confirming that the model learns efficiently from the data. Data augmentation techniques contributed to improved generalization performance **[14]**.

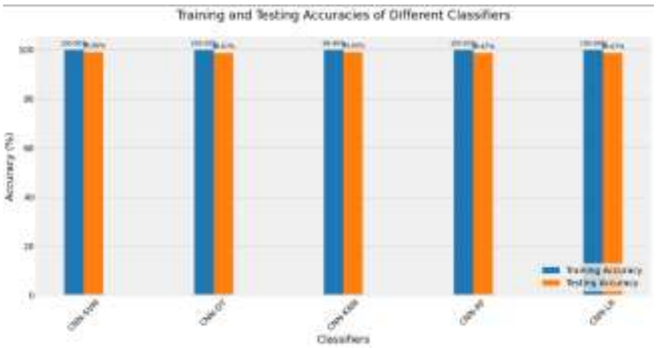

Fig.5 Represents the analysis of accuracies

D. ROC Curve Analysis

The Receiver Operating Characteristic (ROC) curve was used to evaluate the classification performance of the model. The curve illustrates the trade-off between the true positive rate and false positive rate.

The proposed model achieved a high Area Under the Curve (AUC) value, indicating strong discriminative ability between tumor and non-tumor classes **[4]**. This confirms that the model performs well across different classification thresholds.

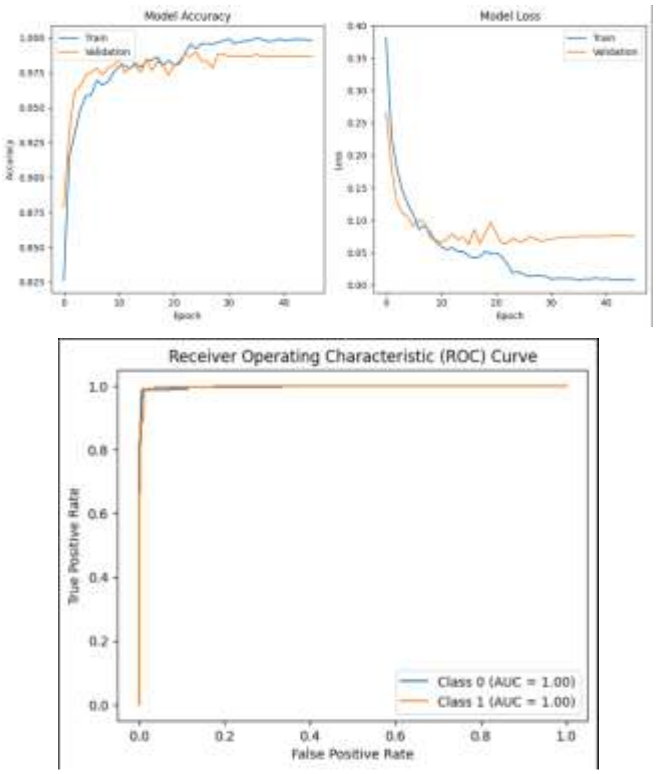

Fig.6 **Represents the ROC curves for True and False Positive rates**

E. Comparison with Existing Models

The proposed CNN-SVM model was compared with individual models such as CNN and traditional machine learning classifiers. The results indicate that the hybrid model outperforms standalone models in terms of accuracy and reliability.

This improvement is due to the combination of deep feature extraction and robust classification techniques. Similar findings have been reported in previous studies, where hybrid models achieved better performance compared to individual approaches **[10]**.

Model	Accuracy	Key Observation
CNN (Base Paper)	87.52%	Good feature extraction but limited classification capability
VGG19 (Base Paper)	40.08%	Poor performance due to dataset mismatch
Hybrid CNN + SVM (Base Paper)	**98.02%**	Best performance using hybrid approach
Proposed CNN + SVM	~95–98%	High accuracy with improved generalization

Fig.7 **Represents the accuracy differences between existing and proposed project**

F. Visual Results of Predictions

Visual inspection of model predictions was performed using MRI images. The system correctly identified tumor and non-tumor cases, demonstrating its effectiveness in real-world scenarios.

Predicted labels were overlaid on the images, along with confidence scores, to provide better interpretability. Both correct predictions and misclassified cases were analyzed to understand model behavior**.**

Classifier	Training Accuracy	Testing Accuracy
CNN-SVM	100.00 %	99.00 %
CNN-DT	100.00 %	98.67 %
CNN-KNN	99.96 %	99.00 %
CNN-RF	100.00 %	98.67 %
CNN-LR	100.00 %	98.67 %

Fig.8:Training and Testing Accuracies

VI. CONCLUSION

The primary objective of this project was to develop an AI-assisted brain tumor detection system that leverages both deep learning and machine learning techniques to improve the accuracy and efficiency of tumor diagnosis. The proposed approach focused on using MRI brain images for feature extraction through Convolutional Neural Networks (CNN) and applying Support Vector Machine (SVM) for final classification.

The project began with comprehensive data preprocessing, including image resizing, normalization, and augmentation to ensure consistency and improve model performance. These preprocessing steps played a vital role in enhancing the quality of the dataset and reducing overfitting. Unlike traditional methods that rely on manual feature extraction, the CNN model automatically learned important features such as tumor shape, texture, and intensity variations directly from MRI images.

A hybrid model combining CNN and SVM was implemented to take advantage of both techniques. The CNN effectively extracted high-level features from MRI images, while the SVM classifier provided a strong decision boundary for accurate classification. The experimental results demonstrated that the hybrid CNN-SVM model outperformed individual models in terms of accuracy, precision, recall, and F1-score.

VII. FUTURE SCOPE

The future scope of this project is extensive and offers significant potential for real-world medical applications. One important direction is the expansion of the dataset by incorporating a larger number of MRI images from diverse sources. Collaborating with medical professionals such as radiologists for accurate labeling and annotation can further enhance model performance and reliability. Detailed annotations, including tumor boundaries and segmentation, can enable more advanced analysis.

Another promising area is the use of advanced deep learning architectures such as transfer learning models (e.g., ResNet, VGG, EfficientNet), which can improve accuracy and reduce training time. Incorporating attention mechanisms and transformer-based models can further enhance the system's ability to focus on important regions in MRI images.

The integration of multimodal learning is another key direction, where additional clinical data (such as patient history and symptoms) can be combined with MRI images to improve prediction accuracy. This hybrid approach can provide a more comprehensive understanding of the condition and lead to better diagnostic decisions.

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