Hybrid CNN–KNN Model for Automated Brain Tumor Detection from MRI Images

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Abstract—**Brain tumors are among the most life-threatening neurological disorders that require early and accurate diagnosis to improve patient survival rates. Magnetic Resonance Imaging (MRI) plays a significant role in detecting abnormalities in brain tissues due to its high resolution and detailed visualization of soft tissues. However, manual examination of MRI scans by radiologists is time-consuming and prone to human error. Therefore, automated computer-aided diagnostic systems have gained increasing attention in medical image analysis. This paper proposes an automated brain tumor detection system using deep learning and machine learning techniques.**

The proposed approach utilizes a Convolutional Neural Network (CNN) for deep feature extraction from MRI images and a K-Nearest Neighbor (KNN) classifier for tumor classification. The system consists of several stages including image preprocessing, segmentation, feature extraction, and classification. Preprocessing techniques such as noise removal, normalization, and contrast enhancement are applied to improve image quality. Statistical and deep features are extracted from the segmented tumor region. The extracted features are then classified into tumor and non-tumor categories using the KNN algorithm. Experimental results demonstrate that the proposed CNN-KNN hybrid model improves classification accuracy and provides reliable tumor detection. The proposed system can assist medical professionals in early diagnosis and reduce the workload of radiologists.

Index Terms—**Brain Tumor Detection, MRI Image Processing, Convolutional Neural Network, K-Nearest Neighbor, Deep Feature Extraction, Medical Image Analysis.**

I. INTRODUCTION

Brain tumors occur due to abnormal growth of cells within brain tissues and may affect the normal functioning of the nervous system. Early detection of brain tumors plays a crucial role in improving the survival rate of patients. Magnetic Resonance Imaging (MRI) is one of the most widely used medical imaging techniques for detecting brain tumors because it provides detailed images of soft tissues without radiation exposure. Traditional diagnosis of MRI images relies heavily on the experience of radiologists, which can sometimes lead to misinterpretation due to the complex structure of brain tissues. With the rapid development of artificial intelligence and machine learning, automated tumor detection systems have gained significant attention in medical image analysis. Image processing techniques combined with machine learning algorithms can assist doctors by automatically identifying abnormal regions in MRI scans. Preprocessing techniques help improve image quality, while feature extraction methods capture important characteristics of tumor regions. Classification algorithms then determine whether the MRI image contains a tumor or not. In this work, a brain tumor detection system using MATLAB is proposed. The system performs preprocessing operations to remove noise and enhance image contrast. Feature extraction techniques are applied to obtain statistical features from the tumor region. A Convolutional Neural Network (CNN) is used to extract deep features from the MRI images, while a K-Nearest Neighbor (KNN) classifier is used for final classification. The main objective of this research is to develop an efficient and accurate system that can assist medical professionals in detecting brain tumors automatically using MRI images.

II. LITERATURE SURVEY

Recent advancements in medical image analysis have significantly improved the detection and classification of brain tumors using Magnetic Resonance Imaging (MRI). Several researchers have applied deep learning and machine learning techniques to enhance the accuracy and reliability of automated tumor detection systems. Saeedi S. et al. (2023) proposed an MRI-based brain tumor detection framework that combines convolutional deep learning models with traditional machine learning techniques. Their study emphasized the effectiveness of deep learning methods in extracting meaningful features from MRI images, which significantly improved tumor classification accuracy. The authors demonstrated that integrating deep learning with machine learning algorithms can provide reliable diagnostic support for medical professionals.

In another study, Bhagwan J. et al. (2024) developed an enhanced Convolutional Neural Network (CNN) model for brain tumor detection from MRI images. Their approach focused on improving feature extraction through multiple convolutional layers and optimized parameters. Experimental results showed that the enhanced CNN model achieved higher classification accuracy and improved tumor detection performance compared to traditional CNN architectures.

Similarly, Karthikeyini C. (2024) introduced an image-processing driven CNN model for precise brain tumor detection. The study applied several preprocessing techniques such as noise removal, normalization, and contrast enhancement to improve MRI image quality before feeding them into the CNN model. The results indicated that proper preprocessing combined with deep learning methods significantly improves tumor detection accuracy.

Research conducted by Vinu M. S. et al. (2024) focused on accurate brain tumor segmentation using enhanced CNN architectures along with machine learning techniques. Their work highlighted the importance of segmentation in isolating the tumor region from MRI images before performing classification. The combination of CNN-based segmentation and machine learning classifiers resulted in improved tumor localization and detection accuracy.

Another important contribution was made by Yadav R. K. et al. (2024), who proposed a modified ResNet-50 convolutional neural network model for brain tumor detection. Their modified architecture enhanced feature extraction capability and improved classification performance. Experimental analysis showed that the proposed model achieved better accuracy compared to conventional CNN models. Lahari A. (2024) investigated the use of CNN architectures for automated brain tumor detection from MRI images. The study demonstrated that deep convolutional networks are capable of learning complex patterns and structural features in medical images, enabling efficient detection of abnormal tissues.

Earlier research by Balaji G. et al. (2022) explored the use of deep convolutional neural networks for tumor detection and classification. Their findings showed that deep learning models outperform traditional image processing methods in terms of accuracy and robustness. Similarly, Zahoor M. M. et al. (2022) proposed a hybrid deep boosted ensemble learning approach for MRI-based brain tumor analysis. The ensemble method improved classification performance by combining multiple deep learning models.

More recently, Khaliki M. Z. and Başarslan M. S. (2024) compared CNN models with transfer learning approaches for brain tumor detection. Their study demonstrated that transfer learning models such as pre-trained CNN architectures can improve performance when trained on limited medical datasets. Additionally, Jadhav R. N. and Sudhaghar G. (2024) presented a comprehensive survey of deep learning approaches for brain tumor detection. The survey highlighted the growing importance of CNN-based models, hybrid frameworks, and ensemble techniques in medical image analysis.

Furthermore, Díaz-Pernas F. J. et al. (2024) proposed a multiscale CNN architecture for brain tumor classification and segmentation. The multiscale approach enabled the model to capture both local and global features of tumor regions in MRI images.

Similarly, Miah J. et al. (2023) investigated a hybrid approach combining CNN with clustering methods for MRI image analysis, which improved tumor region identification and classification accuracy.

From the reviewed literature, it is evident that deep learning models, particularly CNN-based architectures, play a crucial role in automated brain tumor detection. However, many existing approaches rely solely on deep learning models without exploring hybrid combinations with traditional machine learning classifiers. Therefore, the proposed work focuses on a hybrid approach that integrates CNN-based deep feature extraction with the K-Nearest Neighbor (KNN) classifier to improve classification performance and provide reliable brain tumor detection from MRI images.

III. PROPOSED METHODOLOGY

The system combines image processing, deep learning, and machine learning techniques to detect and classify brain tumors from MRI images. The proposed framework consists of several stages including dataset acquisition, image preprocessing, tumor segmentation, feature extraction using Convolutional Neural Networks (CNN), and classification using the K-Nearest Neighbor (KNN) algorithm. Initially, MRI images are collected from an open-source dataset. The images are then preprocessed to improve image quality and remove noise. After preprocessing, segmentation techniques are applied to isolate the tumor region from the MRI image. Deep features are extracted from the segmented images using a CNN model. Finally, the extracted features are classified into tumor and non-tumor categories using the KNN classifier.

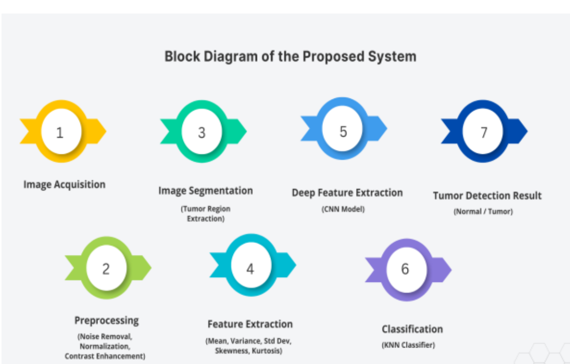

Fig. 1 Flow of proposed model

3.1 Dataset Description:

The dataset used in this study was collected from the open-source Kaggle platform, which provides publicly available medical image datasets for research purposes. The dataset consists of approximately 5000 MRI brain images, including both tumor and normal cases. These images represent different conditions of brain tissues and are used to train and evaluate the proposed tumor detection system. The dataset contains MRI images in standard image formats such as JPEG and PNG. Each image is labeled into one of two categories: tumor or normal (non-tumor). These labeled images enable supervised learning for the classification model.

3.2 Image Preprocessing:

Image preprocessing is an essential step in medical image analysis as it improves the quality of MRI images and enhances important features required for accurate tumor detection. In this study, several preprocessing techniques are applied before performing segmentation and feature extraction. Initially, RGB MRI images are converted into grayscale format. Grayscale conversion simplifies the image representation by reducing the number of channels from three (RGB) to one intensity channel. This helps in reducing computational complexity and improves processing efficiency. After grayscale conversion, all images are resized to 224 × 224 pixels to maintain uniformity across the dataset. Image resizing ensures that all input images have the same dimensions, which is required for CNN-based processing. To reduce unwanted noise present in MRI images, median filtering is applied. Median filtering is an effective noise removal technique that preserves important edges and structural details while eliminating salt-and-pepper noise. This helps in maintaining the clarity of tumor boundaries.

Finally, normalization is performed on the pixel values. In this step, pixel intensity values are scaled to a specific range (usually between 0 and 1). Normalization improves the stability and convergence speed of the CNN during the training process by ensuring consistent input data distribution.

3.3 Image Segmentation:

Image segmentation is used to isolate the tumor region from the brain MRI image. Accurate segmentation helps in identifying the region of interest (ROI) where abnormal tissues may exist. In the proposed system, K-means clustering segmentation is used to separate different regions of the MRI image based on pixel intensity values. K-means is an unsupervised clustering algorithm that groups pixels into clusters with similar characteristics. During the segmentation process, the MRI image is divided into several clusters based on intensity similarity. The cluster that represents abnormal tissue structures is identified as the potential tumor region. This process effectively separates tumor tissues from normal brain tissues.

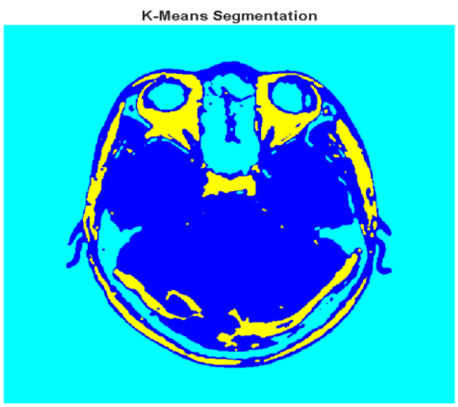

Fig. 2 K - Means Segmented Image

3.4 Feature Extraction Using CNN:
Feature extraction is performed using a Convolutional Neural Network (CNN), which is widely used for analyzing medical images. CNN models are capable of automatically learning important spatial features such as edges, shapes, textures, and patterns from images. The CNN architecture used in this study consists of multiple layers including convolutional layers, activation layers, and pooling layers. The convolutional layers apply several filters to the input image to detect different visual features. These filters scan the image and generate feature maps that represent important structural patterns related to brain tissues and tumor regions. After convolution, an activation function such as the Rectified Linear Unit (ReLU) is applied. The activation function introduces non-linearity into the model, allowing the network to learn complex patterns from MRI images.

Next, pooling layers are used to reduce the spatial dimensions of the feature maps while retaining the most important information. Pooling helps in reducing computational complexity and prevents overfitting. Through multiple convolution and pooling operations, the CNN automatically extracts deep features that represent meaningful characteristics of the tumor region. These extracted features are then passed to the classification stage.

3.5 Classification Using KNN:
The final stage of the proposed system is classification using the K-Nearest Neighbor (KNN) algorithm. KNN is a simple yet effective supervised machine learning algorithm used for pattern recognition and classification tasks. The KNN algorithm works by identifying the k closest neighbors to a given data point in the feature space. It calculates the distance between the test sample and all training samples using a distance measurement method such as Euclidean distance. Once the nearest neighbors are identified, the class label of the majority of the neighbors is assigned to the test sample. In this study, the extracted CNN features are used as input to the KNN classifier. Based on the similarity between feature vectors, the KNN classifier categorizes MRI images into tumor or non-tumor classes. The hybrid combination of CNN feature extraction and KNN classification improves the accuracy and reliability of the brain tumor detection system.

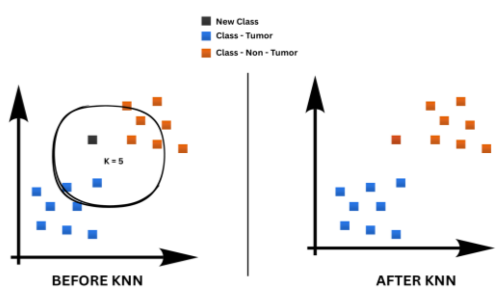

Fig. 3 KNN Algorithm

IV. RESULT AND PERFORMANCE ANALYSIS

The proposed brain tumor detection system was implemented using MATLAB and evaluated using MRI images collected from the Kaggle open-source dataset. The dataset consisted of approximately 5000 MRI images, including both tumor and normal brain scans. The results obtained from each stage of the proposed system, including preprocessing, segmentation, tumor detection, and classification, are presented in this section.

4.1 Preprocessed MRI Images

Before performing segmentation and feature extraction, preprocessing techniques such as grayscale conversion, resizing, noise removal, and normalization were applied to the MRI images. All images were resized to 224 × 224 pixels to maintain uniform input size for the CNN model. Median filtering was applied to remove noise while preserving important edges and structural details of the brain tissues.

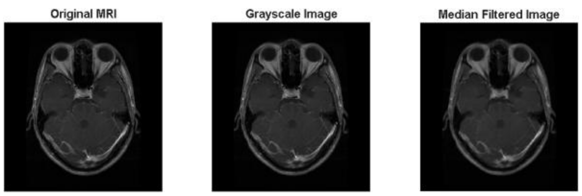

Fig. 4 shows the comparison between the original MRI image and the preprocessed MRI image.

4.2 Tumor Detection and Dimension Measurement

The proposed system successfully detected and highlighted the tumor region in the MRI images. The detected tumor area was marked on the MRI scan, allowing clear visualization of abnormal tissue regions.

Fig. 5 shows the MRI image with the detected tumor region highlighted.

4.3 Accuracy Graph

The performance of the CNN model during training was evaluated using an accuracy graph. The graph represents the variation of classification accuracy across different training epochs.

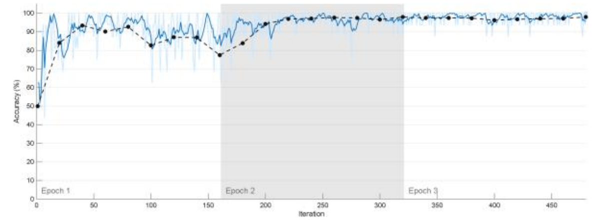

Fig. 6 shows the training accuracy graph of the CNN model.

4.4 Performance Metrics

To evaluate the effectiveness of the proposed brain tumor detection system, several performance metrics were calculated. These include Accuracy, Precision, True Positive Rate (TPR), and True Negative Rate (TNR).

Table 1. Presents the performance metrics obtained from the proposed CNN–KNN model.

Metric	Description
Accuracy	Measures the overall correctness of the classification model
Precision	Indicates the proportion of correctly detected tumor cases
True Positive Rate (TPR)	Measures the ability of the system to correctly detect tumor images
True Negative Rate (TNR)	Measures the ability of the system to correctly classify normal images

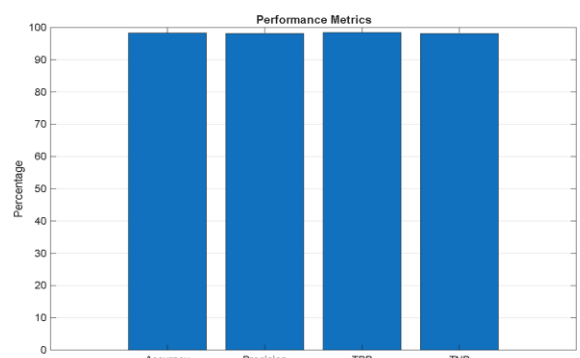

Fig. 7 Performance Metrics

V. DISCUSSION

The Convolutional Neural Network (CNN) used in this study proved effective in extracting deep features from MRI images. CNN models are capable of automatically learning hierarchical features such as edges, shapes, and textures that are associated with tumor structures. These extracted features provided a rich representation of the MRI images, which improved the accuracy of the classification stage. One of the key advantages of the proposed approach is the hybrid integration of CNN and K-Nearest Neighbor (KNN) algorithms. While CNN efficiently performs deep feature extraction, the KNN classifier is simple, robust, and effective for classification tasks based on feature similarity. The combination of these two techniques enhances the overall performance of the system by leveraging the strengths of both deep learning and traditional machine learning methods. In addition, the hybrid model reduces the complexity associated with fully deep neural network classifiers while still achieving reliable classification accuracy.

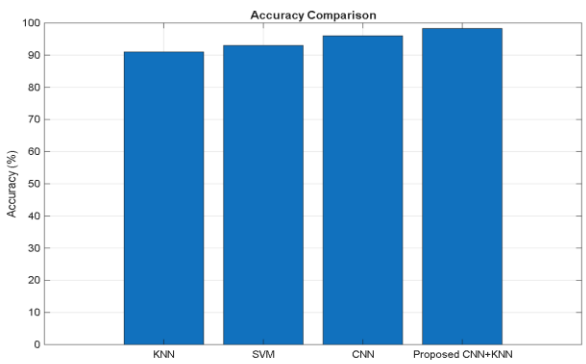

Fig. 8 Accuracy Comparison

When compared with existing brain tumor detection methods that rely solely on CNN or traditional machine learning algorithms, the proposed CNN–KNN hybrid approach provides improved detection performance and reliable classification results. Several previous studies have focused only on deep learning architectures, which require large training datasets and high computational resources. In contrast, the proposed system utilizes CNN primarily for feature extraction while employing KNN for classification, resulting in an efficient and accurate detection framework.

Overall, the experimental findings indicate that the proposed approach successfully detects tumor regions, identifies tumor dimensions, and accurately classifies MRI images. The system demonstrates the potential to serve as a computer-aided diagnostic tool that can assist radiologists in early detection of brain tumors and reduce manual workload in medical imaging analysis.

VI. CONCLUSION

In this study, an automated brain tumor detection system based on a hybrid combination of Convolutional Neural Networks (CNN) and the K-Nearest Neighbor (KNN) algorithm was proposed for analyzing MRI brain images. The system integrates several important stages including image preprocessing, tumor segmentation, deep feature extraction, and classification. MRI images collected from an open-source Kaggle dataset containing approximately 5000 samples were used to evaluate the performance of the proposed approach.

Initially, preprocessing techniques such as grayscale conversion, image resizing, median filtering, and normalization were applied to improve image quality and reduce noise. K-means clustering segmentation was then used to isolate the tumor region and identify the region of interest (ROI) from the MRI images. Deep features were extracted from the segmented images using a CNN model, which effectively captured important structural and texture characteristics of tumor regions. The extracted features were subsequently classified using the KNN algorithm to distinguish between tumor and non-tumor images. The experimental results demonstrated that the proposed CNN–KNN hybrid model successfully detects tumor regions, highlights the tumor location in MRI images, and determines the dimension of the detected tumor. The system also achieved strong classification performance as shown by the accuracy graph and performance metrics. These results indicate that the proposed method provides reliable and efficient tumor detection.

Overall, the proposed framework can serve as a computer-aided diagnostic system to assist radiologists in the early detection of brain tumors. By automating the detection process, the system can reduce diagnostic time, minimize human error, and improve decision-making in medical imaging analysis.

REFERENCES

[1] Saeedi, S., Rezayi, S., Keshavarz, H., & Niakan Kalhori, S. (2023). MRI-based brain tumor detection using convolutional deep learning methods and machine learning techniques. BMC

Medical Informatics and Decision Making, 23(16).

[2] Bhagwan, J., Rani, S., Kumar, S., Chaba, Y., Godara, S., & Sindhu, S. (2024). An Enhanced CNN Model for Brain Tumor Detection from MRI Images. Journal of Electrical Systems.

[3] Karthikeyini, C. (2024). Image Processing Driven CNN Model for Precise Brain Tumor Detection in MRI Data. International Journal of Intelligent Systems and Applications in Engineering.

[4] Vinu, M. S., Pasupathy, V., Senthilkumar, K. P., & Balasubramanian, K. (2024). Accurate Brain Tumour Segmentation in MRI Images using Enhanced CNN and Machine Learning Methods. IJISAE.

[5] Yadav, R. K., Mishra, A. K., Saini, D. K., & Pant, H. (2024). Brain Tumor Detection using Modified ResNet-50 CNN Model. Indian Journal of Information Sources and Services.

[6] Lahari, A. (2024). Brain Tumor Detection using Convolutional Neural Networks. Indian Journal of Engineering Research Networking and Development.

[7] Balaji, G., Sen, R., & Kirty, H. (2022). Detection and Classification of Brain Tumors Using Deep Convolutional Neural Networks. arXiv.

[8] Zahoor, M. M., Qureshi, S. A., Khan, S. H., & Khan, A. (2022). Hybrid Deep Boosted Ensemble Learning for Brain Tumor Analysis using MRI. arXiv.

[9] Saeedi, S., Rezayi, S., Keshavarz, H., & Niakan Kalhori, S. (2023). MRI-based brain tumor detection using convolutional deep learning methods and machine learning techniques. BMC Medical Informatics and Decision Making, 23(16).

[10] Khaliki, M. Z., & Başarslan, M. S. (2024). Brain tumor detection from images and comparison with transfer learning methods and CNN. Scientific Reports, 14, 2664.

[11] Yadav, R. K., Mishra, A. K., Saini, D. K., & Pant, H. (2024). A model for brain tumor detection using a modified ResNet-50 convolution layer. Indian Journal of Information Sources and Services.

[12] Bhagwan, J., Rani, S., Kumar, S., Chaba, Y., Godara, S., & Sindhu, S. (2024). An enhanced CNN model for brain tumor detection from MRI images. Journal of Electrical Systems.

[13] Karthikeyini, C. (2024). An image processing-driven CNN model for precise brain tumor detection in MRI data. International Journal of Intelligent Systems and Applications in Engineering.

[14] Vinu, M. S., Pasupathy, V., Senthilkumar, K. P., & Balasubramanian, K. (2024). Accurate brain tumour segmentation in MRI images using enhanced CNN and machine learning methods. International Journal of Intelligent Systems and Applications in Engineering.

[15] Jadhav, R. N., & Sudhaghar, G. (2024). Deep learning approaches for brain tumor detection in MRI images: A comprehensive survey. International Journal of Intelligent Systems and Applications in Engineering.

[16] Lahari, A. (2024). Brain tumor detection using convolutional neural networks. Indian Journal of Engineering Research Networking and Development.

[17] Díaz-Pernas, F. J., Martínez-Zarzuela, M., Antón-Rodríguez, M., & González-Ortega, D. (2024). A deep learning approach for brain tumor classification and segmentation using multiscale CNN. arXiv preprint.