



Brain Tumor Detection

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Abstract: This paper presents a brain tumor detection system designed to assist early diagnosis using a multi-model machine learning approach. The system integrates MRI image analysis using Convolutional Neural Network (CNN) and symptom-based prediction using Random Forest. It combines both medical imaging and clinical data to improve accuracy and reliability. The system is implemented as a web-based application that allows users to upload MRI images or enter symptoms for preliminary screening. It targets healthcare support by providing fast, accessible, and effective tumor detection.

Keywords: Brain Tumor Detection, Machine Learning, Deep Learning, Convolutional Neural Network, Random Forest, MRI, Medical Image Analysis, Web Application.

I. INTRODUCTION

Brain tumor is a serious neurological condition caused by abnormal growth of cells in the brain. Early detection is important as it helps in effective treatment and improves survival rates. However, traditional diagnosis using MRI and expert analysis is time-consuming and may lead to errors.

With the advancement of Artificial Intelligence (AI) and Machine Learning (ML), automated systems can assist in faster and more accurate detection. Convolutional Neural Networks (CNNs) are effective in analyzing MRI images, while algorithms like Random Forest help in predicting tumor risk based on symptoms.

This paper proposes a brain tumor detection system that combines MRI image analysis and symptom-based prediction using a multi-model approach. The system is developed as a web-based application to provide quick and accessible preliminary screening.

II. LITERATURE REVIEW

With the increasing use of Artificial Intelligence in healthcare, brain tumor detection has gained significant attention. Traditional diagnosis methods rely on MRI analysis by experts, which can be time-consuming and prone to human error.

Deep learning techniques, especially Convolutional Neural Networks (CNNs), have shown high accuracy in analyzing medical images and detecting tumors. Many studies have used pre-trained models to improve performance in MRI-based classification tasks.

In addition, machine learning algorithms such as Random Forest and Support Vector Machines (SVM) are effective in predicting diseases based on patient symptoms and clinical data.

Recent research also focuses on combining image-based and symptom-based approaches to improve overall accuracy. However, there is still a need for systems that provide both accuracy and accessibility through user-friendly platforms.

III. PROPOSED SYSTEM

The proposed system is a web-based brain tumor detection platform designed to assist in early and accurate diagnosis using a multi-model machine learning approach. The system focuses on improving detection by combining MRI image analysis with symptom-based prediction, providing a more reliable result compared to single-method systems.

The system is divided into two main components. The first component uses a Convolutional Neural Network (CNN) to analyze brain MRI images and identify tumor patterns. The CNN model processes the images, extracts important features,



and classifies them as tumor or non-tumor. The second component uses a Random Forest classifier to analyze patient symptoms such as headache, seizures, vision problems, and other clinical factors to predict the risk of a tumor.

The platform provides a user-friendly interface where users can upload MRI images or enter symptoms for analysis. After processing the input, the system generates a prediction along with a confidence score, helping users understand the likelihood of a tumor.

To enhance accuracy, both models work together and provide a combined result, making the system more effective and dependable. The system also ensures fast response time, making it suitable for real-time preliminary screening.

Overall, the proposed system aims to provide a simple, accessible, and efficient solution for brain tumor detection. It can assist healthcare professionals in decision-making and improve early diagnosis, especially in areas with limited medical resources.

IV. SYSTEM ARCHITECTURE

The proposed system follows a structured architecture to ensure efficient processing, accuracy, and scalability. It is divided into three main layers: Presentation Layer, Processing Layer, and Data Layer.

1. Presentation Layer (Frontend)

This layer acts as the user interface of the system. It allows users to interact with the platform through a web browser.

- Users can upload MRI images or enter symptoms
- Displays prediction results and confidence scores
- Provides a simple and user-friendly interface
- Ensures accessibility across different devices

2. Processing Layer (Model Layer)

This layer is responsible for handling all computations and predictions. It consists of two main models:

- CNN Model: Analyzes MRI images and detects tumor patterns
- Random Forest Model: Evaluates patient symptoms and predicts tumor risk

Both models process the input data and generate predictions, which are then combined to improve overall accuracy and reliability.

3. Data Layer (Database)

This layer stores all necessary data required for the system.

- Stores MRI datasets used for training
- Maintains symptom data and model parameters
- Saves user inputs and prediction results (if required)

4. System Workflow

1. User accesses the web application
2. Inputs MRI image or symptoms
3. Data is sent to the processing layer
4. Models analyze the input and generate predictions
5. Final result is displayed to the user

5. Key Features of Architecture

- Scalability: Supports multiple users simultaneously
- Accuracy: Combines two models for better results
- Efficiency: Provides fast and real-time predictions
- Accessibility: Web-based system usable from anywhere



V. METHODOLOGY

The proposed system is developed using a systematic and structured methodology to ensure accuracy, reliability, and effectiveness in brain tumor detection. The process begins with the requirement analysis phase, where user needs are carefully studied and key aspects such as MRI image analysis and symptom-based prediction are identified. Both functional requirements (e.g., image upload, symptom input, prediction generation, and result display) and nonfunctional requirements (e.g., usability, performance, and scalability) are defined to establish a strong foundation for system development.

This is followed by the system design phase, in which the overall architecture, user interface, and data flow are planned. The system is designed using a modular approach to ensure flexibility and easy maintenance. The user interface is created to provide a simple and intuitive experience, allowing users to upload MRI images or enter symptoms easily. Additionally, the structure of the CNN model and Random Forest model, along with data processing steps, are carefully organized to ensure efficient and accurate prediction.

Subsequently, the development phase involves the implementation of both frontend and backend components. The frontend is developed using standard web technologies to create an interactive and responsive interface, while the backend handles core functionalities such as image preprocessing, feature extraction, symptom analysis, and prediction generation. The system integrates a Convolutional Neural Network (CNN) for MRI image classification and a Random Forest classifier for symptom-based analysis. APIs are used to ensure smooth communication between the frontend and backend components.

Following development, the system undergoes testing and validation, where various testing methods such as functional testing, performance testing, and usability testing are conducted. This phase ensures that all components of the system operate correctly, the predictions are accurate, and the user interface is easy to use. Any identified issues or errors are resolved to improve overall system performance and reliability.

Finally, the system is deployed as a web-based application, allowing users to access it anytime and from any device with an internet connection. Post-deployment, continuous monitoring and evaluation are carried out using system performance metrics and user feedback. This helps in identifying areas for improvement and ensures that the system remains effective, accurate, and capable of supporting early brain tumor detection over time.

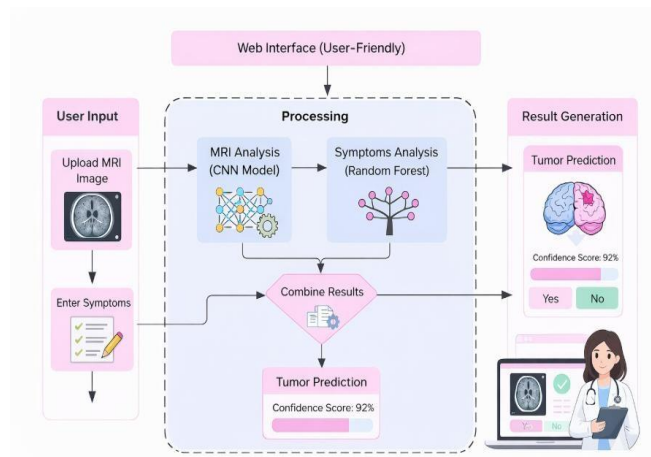


Fig 1 Flow Chart

VI. RESULTS AND DISCUSSION

The increasing complexity of medical conditions such as brain tumors requires accurate and timely diagnosis, while traditional methods based on manual MRI analysis can be time-consuming and prone to human error. To address this challenge, a web-based brain tumor detection system using a multi-model machine learning approach was developed and its effectiveness was evaluated through model performance and prediction analysis.

The results indicate a significant improvement in detection accuracy and system performance. The Convolutional Neural Network (CNN) model effectively analyzed MRI images and identified tumor patterns, while the Random Forest model provided reliable predictions based on patient symptoms. The combination of both models played a crucial role in improving overall accuracy and reliability of the system. Additionally, performance evaluation shows consistent and



stable results, indicating effective learning and generalization of the models. The system provides fast and real-time predictions, allowing users to obtain results quickly through a web-based interface.

A comparative analysis between individual model performance and the combined multi-model approach clearly shows a positive improvement, highlighting the effectiveness of the proposed system in brain tumor detection. The combined system reduces the chances of misclassification and enhances diagnostic support for early detection.

The overall results validate that the integration of machine learning and deep learning techniques significantly improves accuracy, efficiency, and reliability in brain tumor detection. The system serves as a useful tool for preliminary screening and supports healthcare professionals in decision-making.

VII. FUTURE WORK

Although the proposed brain tumor detection system demonstrates promising results using a multi-model machine learning approach, there are several areas where further improvements can be made to enhance its performance and real-world applicability. Future work can focus on expanding the system by incorporating larger and more diverse MRI datasets to improve model accuracy and generalization across different patient conditions.

The system can also be enhanced by using advanced deep learning architectures such as ResNet, EfficientNet, or DenseNet to achieve better feature extraction and classification performance. Additionally, the current system performs binary classification (tumor vs. non-tumor), and future improvements can include multi-class classification to identify different types of brain tumors such as benign and malignant.

Another potential improvement is the integration of explainable AI techniques such as Grad-CAM or SHAP, which can help visualize model decisions and increase trust among healthcare professionals. The system can also be extended to include tumor segmentation to accurately locate the tumor region within MRI images.

Furthermore, the platform can be enhanced by integrating additional medical data such as patient history, genetic information, and laboratory reports to provide a more comprehensive diagnostic system. Deployment as a mobile application and integration with hospital management systems can improve accessibility and real-time usability.

Finally, future research can focus on clinical validation through real-world testing and user feedback to ensure reliability and compliance with medical standards. Continuous updates and improvements will help the system evolve into a more robust and widely applicable solution for brain tumor detection.

VIII. CONCLUSION

In conclusion, brain tumor detection is a crucial and challenging task in the field of medical diagnosis, as early identification plays a vital role in improving patient survival rates and treatment effectiveness. Traditional diagnostic methods primarily rely on MRI scans and expert interpretation, which can be time-consuming, costly, and sometimes prone to human error. These limitations highlight the need for intelligent and automated systems that can assist healthcare professionals in making faster and more accurate decisions.

The proposed system presents a multi-model machine learning approach for brain tumor detection by integrating Convolutional Neural Networks (CNN) for MRI image analysis and Random Forest for symptom-based prediction. The CNN model effectively extracts important features from MRI images and identifies tumor patterns, while the Random Forest model analyzes clinical symptoms to estimate the risk of tumor presence. By combining both image-based and symptom-based analysis, the system provides a more comprehensive and reliable diagnostic solution compared to single-model approaches.

The experimental results demonstrate that the system achieves good accuracy and performance in detecting tumor and non-tumor cases. The integration of both models significantly improves prediction reliability and reduces the chances of misclassification. Additionally, the system provides fast and real-time results through a web-based interface, making it easily accessible and user-friendly for preliminary screening.

Furthermore, the proposed system reduces dependency on manual analysis and supports healthcare professionals in decision-making by providing an additional layer of diagnostic assistance. It is especially beneficial in resource-limited



environments where access to expert radiologists may be limited. The system also highlights the importance of combining artificial intelligence with medical data to enhance diagnostic efficiency and accuracy.

Overall, the proposed brain tumor detection system serves as an effective, scalable, and practical solution for early diagnosis. With further improvements such as advanced deep learning models, larger datasets, and real-world clinical validation, the system has strong potential to be adopted in healthcare environments and contribute to improved medical outcomes.

REFERENCES

- [1] H. Sung, J. Ferlay, R. L. Siegel et al., "Global cancer statistics 2020: GLOBOCAN estimates of incidence and mortality worldwide," *CA: A Cancer Journal for Clinicians*, vol. 71, no. 3, pp. 209–249, 2021.
- [2] G. Litjens et al., "A survey on deep learning in medical image analysis," *Medical Image Analysis*, vol. 42, pp. 60–88, 2017.
- [3] M. Havaei et al., "Brain tumor segmentation with deep neural networks," *Medical Image Analysis*, vol. 35, pp. 18–31, 2017.
- [4] S. Pereira et al., "Brain tumor segmentation using convolutional neural networks in MRI images," *IEEE Transactions on Medical Imaging*, vol. 35, no. 5, pp. 1240–1251, 2016.
- [5] A. Krizhevsky, I. Sutskever, and G. Hinton, "ImageNet classification with deep convolutional neural networks," in *Proc. NIPS*, 2012.
- [6] Y. LeCun, Y. Bengio, and G. Hinton, "Deep learning," *Nature*, vol. 521, no. 7553, pp. 436–444, 2015.
- [7] L. Breiman, "Random forests," *Machine Learning*, vol. 45, no. 1, pp. 5–32, 2001.
- [8] K. He, X. Zhang, S. Ren, and J. Sun, "Deep residual learning for image recognition," in *Proc. IEEE CVPR*, 2016.
- [9] S. Bauer et al., "A survey of MRI-based medical image analysis for brain tumor studies," *Physics in Medicine & Biology*, vol. 58, no. 13, pp. 97–129, 2013.
- [10] B. Menze et al., "The Multimodal Brain Tumor Image Segmentation Benchmark (BRATS)," *IEEE Transactions on Medical Imaging*, vol. 34, no. 10, pp. 1993–2024, 2015.