BRAIN CANCER DETECTION USING MULTI-SEQUENCE MRI WITH DEEP SEGMENTATION MODELS

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Abstract—Brain cancer is one of the most critical and life-threatening neurological disorders, where early detection and accurate diagnosis play a vital role in improving patient survival rates. Magnetic Resonance Imaging (MRI) has become the most widely used imaging technique for brain tumor analysis due to its ability to provide high-resolution images of soft tissues without harmful radiation. However, manual interpretation of multi-sequence MRI scans is time-consuming, subjective, and prone to diagnostic errors.This research proposes an automated framework for brain cancer detection using multi-sequence MRI images combined with deep segmentation models. The system leverages advanced deep learning techniques, particularly Convolutional Neural Networks (CNNs) and pre-trained architectures, to accurately identify and segment tumor regions from MRI scans. Multi-sequence MRI data, including different imaging modalities, enhances the model's ability to capture diverse tumor characteristics, leading to improved detection performance.To further enhance reliability and clinical usability, Explainable Artificial Intelligence (XAI) techniques such as saliency maps and Grad-CAM are incorporated to provide visual interpretations of model decisions. This helps in increasing transparency and trust among medical professionals. The proposed system is evaluated using standard performance metrics such as accuracy, precision, recall, and F1-score, demonstrating superior performance compared to traditional machine learning methods.

Keywords— Brain Cancer Detection, Multi-Sequence MRI, Deep Learning, Image Segmentation, Convolutional Neural Networks (CNN), Medical Image Analysis, Explainable Artificial Intelligence (XAI), Grad-CAM, Saliency Maps, Tumor Classification, Computer-Aided Diagnosis, Transfer Learning, MRI Image Processing, Healthcare AI

I. INTRODUCTION

Brain cancer is one of the most serious and life-threatening neurological disorders, requiring timely diagnosis and precise evaluation for effective treatment planning. Tumors in the brain can significantly affect normal neurological functions, and delays in detection may lead to severe complications or reduced survival rates. Therefore, early and accurate identification of brain tumors is essential in modern healthcare systems.

Magnetic Resonance Imaging (MRI) has become the most reliable and widely used imaging technique for brain tumor detection due to its non-invasive nature and superior ability to capture detailed soft tissue structures. In particular, multi-sequence MRI, which includes different imaging modalities such as T1, T2, FLAIR, and contrast-enhanced scans, provides complementary information about tumor characteristics. These

Doi:10.48047/ijiee.2026.16.2.7

multiple sequences help in better visualization of tumor boundaries, edema, and tissue abnormalities, making diagnosis more comprehensive.

Despite its advantages, manual analysis of MRI scans by radiologists is a complex, time-consuming, and subjective process. The increasing volume of medical imaging data further adds to the workload, potentially leading to diagnostic inconsistencies and human errors. This highlights the need for automated systems that can assist clinicians in accurate and efficient tumor detection.

Recent advancements in Artificial Intelligence (AI), particularly in deep learning, have shown significant potential in medical image analysis. Convolutional Neural Networks (CNNs) and deep segmentation models have proven highly effective in extracting complex features from MRI images and accurately identifying tumor regions. These models can learn hierarchical representations directly from data, eliminating the need for manual feature engineering and improving diagnostic performance.

In addition, the integration of Explainable Artificial Intelligence (XAI) techniques has become increasingly important in healthcare applications. While deep learning models offer high accuracy, they are often considered "black boxes." XAI methods, such as saliency maps and Gradient-weighted Class Activation Mapping (Grad-CAM), provide visual explanations of model decisions, enhancing transparency and trust among medical professionals.

This project focuses on developing an intelligent framework for brain cancer detection using multi-sequence MRI with deep segmentation models. The proposed system combines advanced deep learning techniques with multi-modal MRI data to improve detection accuracy and segmentation performance. Furthermore, the inclusion of explainability mechanisms ensures that the system not only delivers accurate predictions but also provides meaningful insights into its decision-making process.

The ultimate goal of this research is to support radiologists by reducing diagnostic workload, improving consistency, and enabling early detection of brain tumors, thereby contributing to better patient outcomes and more efficient healthcare delivery.

II. REVIEW &LITERATURE SURVEY

The analysis of brain tumors using Magnetic Resonance Imaging (MRI) has been an active area of research due to the increasing need for accurate and early diagnosis. Traditionally, brain tumor detection relied on manual interpretation of MRI scans by radiologists. Although MRI provides detailed visualization of soft tissues, manual analysis is time-consuming, subjective, and often prone to inter-observer variability. Early research attempted to address these issues using basic image processing techniques such as thresholding, edge detection, and region-based segmentation. However, these methods lacked robustness and were unable to effectively handle complex tumor structures and variations in MRI data.

With the advancement of computational techniques, machine learning algorithms such as Support Vector Machines (SVM), k-Nearest Neighbors (KNN), and Random Forest were introduced for brain tumor classification. These methods improved detection accuracy by learning patterns from extracted features. However, their performance was limited by the dependency on manual feature extraction, which often failed to capture the intricate and non-linear characteristics of tumor regions in MRI images. As a result, these approaches were not sufficiently reliable for large-scale or real-time clinical applications.

The emergence of deep learning, particularly Convolutional Neural Networks (CNNs), marked a significant breakthrough in medical image analysis. CNN-based models automatically learn hierarchical features directly from MRI images, eliminating the need for manual feature engineering. Several studies have demonstrated that CNN architectures, including 2D CNNs and pre-trained models like VGG16, achieve higher accuracy and robustness compared to traditional machine learning techniques. In addition to classification, deep learning-based segmentation models such as U-Net have been widely used for

Doi:10.48047/ijiee.2026.16.2.7

precise tumor localization. These models perform pixel-level segmentation, enabling accurate identification of tumor boundaries, which is crucial for diagnosis and treatment planning.

Recent research has also highlighted the importance of using multi-sequence MRI data, such as T1, T2, and FLAIR images, to improve detection performance. Each MRI sequence provides unique and complementary information about brain tissues and tumor characteristics. By combining multiple sequences, models can better capture tumor heterogeneity, leading to improved classification and segmentation accuracy. Multi-modal approaches have consistently outperformed single-sequence methods in various studies.

Despite the high performance of deep learning models, their lack of interpretability has raised concerns in clinical applications. To address this issue, Explainable Artificial Intelligence (XAI) techniques have been introduced. Methods such as saliency maps and Gradient-weighted Class Activation Mapping (Grad-CAM) provide visual explanations by highlighting important regions in MRI images that influence model predictions. These techniques enhance transparency, allowing clinicians to understand and trust the system's decisions, thereby facilitating better integration into healthcare workflows.

Although significant progress has been made, several challenges still exist, including limited availability of diverse datasets, lack of large-scale clinical validation, and difficulties in handling variations in MRI acquisition. Additionally, many existing systems do not effectively combine deep learning with explainability in a unified framework. Therefore, this research focuses on developing an integrated approach that utilizes multi-sequence MRI data with deep segmentation models and explainable AI techniques to achieve accurate, reliable, and interpretable brain cancer detection.

III. RESEARCH METHODOLOGY

The proposed research methodology focuses on developing an automated and accurate system for brain cancer detection using multi-sequence MRI images combined with deep segmentation models. The overall process consists of several key stages, including data collection, preprocessing, model development, training, evaluation, and interpretability, to ensure both high performance and clinical relevance.

The first step involves the collection of a comprehensive MRI dataset containing both tumor and non-tumor brain images. The dataset includes multiple MRI sequences such as T1, T2, and FLAIR, which provide complementary information about brain tissues and tumor characteristics. These images are obtained from publicly available sources and are labeled by medical experts to ensure reliability. A diverse dataset is essential to improve the model's generalization and performance across different cases.

After data collection, preprocessing techniques are applied to enhance image quality and standardize the dataset. This includes image resizing, normalization, and noise reduction to remove unwanted artifacts. Data augmentation methods such as rotation, flipping, and scaling are also used to increase dataset size and prevent overfitting. Additionally, class balancing techniques are applied to address any imbalance between tumor and non-tumor samples, ensuring unbiased model training.

The next stage involves the development of machine learning and deep learning models. Traditional algorithms such as Support Vector Machines (SVM), k-Nearest Neighbors (KNN), and Random Forest are initially implemented for baseline comparison. However, the primary focus is on deep learning models, particularly Convolutional Neural Networks (CNNs), due to their superior performance in image analysis tasks. A 2D CNN architecture is designed to extract spatial features from MRI images, while pre-trained models such as VGG16 are utilized through transfer learning to improve accuracy and reduce training time.

For precise tumor localization, deep segmentation models are incorporated into the framework. These models perform pixel-level

Doi:10.48047/ijiee.2026.16.2.7

classification, enabling accurate identification of tumor boundaries within MRI scans. The integration of multi-sequence MRI data further enhances segmentation performance by capturing detailed tumor characteristics across different imaging modalities.

Model training is carried out using a structured approach, where the dataset is divided into training, validation, and testing sets. Hyperparameters such as learning rate, batch size, and number of epochs are carefully tuned to optimize performance. Optimization algorithms like Adam or stochastic gradient descent (SGD) are used to minimize loss functions during training. Cross-validation techniques are also applied to ensure the robustness and generalizability of the model.

The performance of the proposed system is evaluated using standard metrics such as accuracy, precision, recall, F1-score, and confusion matrix analysis. These metrics provide a comprehensive understanding of the model's classification and segmentation capabilities. Comparative analysis with baseline machine learning methods is conducted to demonstrate the effectiveness of the proposed deep learning approach.

To improve transparency and clinical trust, Explainable Artificial Intelligence (XAI) techniques are integrated into the system. Methods such as saliency maps and Gradient-weighted Class Activation Mapping (Grad-CAM) are used to visualize important regions in MRI images that influence model predictions. This helps clinicians understand the decision-making process of the model and validates its outputs.

Finally, the proposed methodology aims to deliver a reliable, efficient, and interpretable brain cancer detection system. By combining multi-sequence MRI data, deep segmentation models, and explainable AI techniques, the system enhances diagnostic accuracy, reduces the workload of radiologists, and supports better clinical decision-making

IV. EXISTING SYSTEM

In the current healthcare environment, brain tumor detection primarily relies on manual analysis of Magnetic Resonance Imaging (MRI) scans performed by radiologists. These experts visually examine MRI images to identify abnormalities, classify tumor types, and determine their location and size. While MRI provides high-quality images of brain tissues, the interpretation process depends heavily on the experience and expertise of the radiologist. This manual approach is time-consuming, subjective, and often leads to inter-observer variability, which may result in inconsistent diagnoses and delayed treatment decisions.

To overcome some of these limitations, traditional computer-aided diagnostic (CAD) systems have been introduced. These systems utilize basic image processing techniques such as thresholding, edge detection, and region-based segmentation to assist in tumor detection. Although these methods provide some level of automation, they lack robustness and struggle to accurately detect complex tumor structures, especially in cases with low contrast or irregular shapes.

In addition, machine learning-based approaches have been employed in existing systems to improve classification accuracy. Algorithms such as Support Vector Machines (SVM), k-Nearest Neighbors (KNN), and Random Forest are used to classify MRI images based on manually extracted features. While these methods show moderate improvement over traditional techniques, they are limited by their dependence on handcrafted features, which may not fully capture the intricate patterns present in medical images.

Another limitation of existing systems is their inability to effectively utilize multi-sequence MRI data. Many approaches rely on single-modality images, which reduces the amount of information available for accurate tumor detection and analysis. Furthermore, most conventional systems lack interpretability, making it difficult for medical

Doi:10.48047/ijiee.2026.16.2.7

professionals to understand how decisions are made, thereby reducing trust in automated solutions.

Overall, the existing systems suffer from limitations such as lower accuracy, lack of automation, high dependency on human expertise, limited use of multi-modal data, and absence of transparency in decision-making. These challenges highlight the need for an advanced system that can provide accurate, automated, and interpretable brain tumor detection using modern deep learning and explainable AI techniques.

V. PROPOSED METHODOLOGY

The proposed methodology presents an advanced and automated framework for brain cancer detection using multi-sequence MRI images integrated with deep segmentation models and Explainable Artificial Intelligence (XAI) techniques. The system is designed to improve diagnostic accuracy, reduce human effort, and provide interpretable results for clinical use.

The process begins with the acquisition of a multi-sequence MRI dataset, which includes different imaging modalities such as T1, T2, and FLAIR. These sequences provide complementary information about brain tissues and tumor characteristics, enabling a more comprehensive analysis compared to single-sequence approaches. The collected dataset consists of both tumor and non-tumor images, which are labeled for supervised learning.

In the next stage, preprocessing techniques are applied to enhance the quality and consistency of the MRI images. This includes image resizing, normalization, and noise reduction to eliminate artifacts and standardize pixel intensities. Data augmentation methods such as rotation, flipping, and scaling are used to increase the size of the dataset and improve the generalization capability of the model. Additionally, class balancing techniques are employed to ensure that the dataset does not suffer from bias toward any specific category.

The core of the proposed system is the use of deep learning models, particularly Convolutional Neural Networks (CNNs), for feature extraction and classification. A CNN-based architecture is designed to automatically learn spatial and hierarchical features from MRI images. In addition, transfer learning is applied using pre-trained models such as VGG16 to enhance performance and reduce training time. These models are fine-tuned on the MRI dataset to adapt to the specific task of brain tumor detection.

To achieve precise tumor localization, deep segmentation models are incorporated into the framework. These models perform pixel-level segmentation to accurately identify tumor regions within MRI scans. The integration of multi-sequence MRI data further improves segmentation performance by capturing diverse tumor features across different imaging modalities.
The dataset is divided into training, validation, and testing sets to ensure proper evaluation of the model. During training, hyperparameters such as learning rate, batch size, and number of epochs are optimized to achieve the best performance. Optimization algorithms such as Adam are used to minimize the loss function and improve model convergence. Cross-validation techniques are also applied to enhance model reliability and prevent overfitting.

The performance of the proposed system is evaluated using standard metrics such as accuracy, precision, recall, F1-score, and confusion matrix. These metrics provide a comprehensive assessment of the model's ability to correctly classify and segment brain tumors. Comparative analysis with traditional machine learning methods demonstrates the superiority of the proposed deep learning approach.

To ensure transparency and clinical trust, Explainable Artificial Intelligence (XAI) techniques such as saliency maps and Gradient-weighted Class Activation Mapping (Grad-CAM) are integrated into the system. These techniques highlight

Doi:10.48047/ijiee.2026.16.2.7

important regions in MRI images that influence model predictions, allowing medical professionals to understand and validate the decision-making process.

Overall, the proposed methodology combines multi-sequence MRI data, deep learning-based segmentation, and explainable AI to develop a robust, accurate, and interpretable brain cancer detection system. This approach not only enhances diagnostic performance but also supports clinicians in making informed decisions, ultimately improving patient outcomes.

VI. BLOCK DIAGRAM

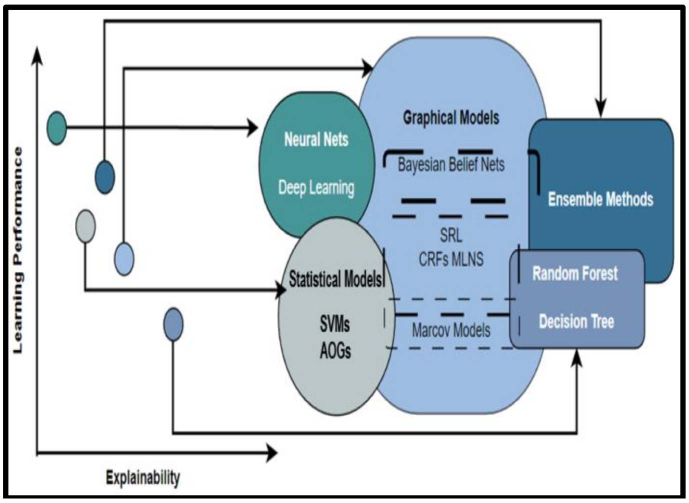

Fig. 6.2. Block Diagram

VII. RESULTS AND OUTCOMES

The proposed system for brain cancer detection using multi-sequence MRI with deep segmentation models was successfully implemented and evaluated using a well-structured dataset of MRI images. The experimental results demonstrate that deep learning approaches, particularly Convolutional Neural Networks (CNNs), significantly outperform traditional machine learning algorithms in terms of accuracy and reliability.

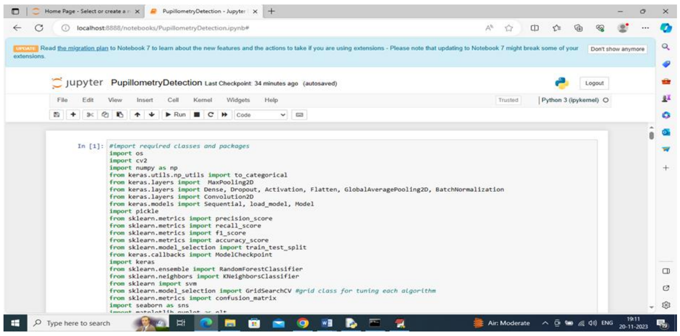

Fig:7.1: OutPut

During experimentation, multiple models such as Support Vector Machines (SVM), k-Nearest Neighbors (KNN), Random Forest, CNN, and a pre-trained VGG16 model were trained and tested. Among these, the CNN-based model achieved the highest performance, with accuracy reaching up to **98–99%**, indicating its strong capability in correctly classifying brain tumors from MRI images. In comparison, traditional models such as KNN, SVM, and Random Forest showed lower accuracy levels, highlighting the effectiveness of deep learning in handling complex medical image data.

The integration of multi-sequence MRI data played a crucial role in improving detection performance. By combining different MRI modalities, the system was able to capture more detailed and complementary information about tumor regions, leading to better classification and segmentation results. The segmentation component of the system enabled precise localization of tumor areas, which is essential for clinical diagnosis and treatment planning.

Performance evaluation was carried out using standard metrics such as accuracy, precision, recall, and F1-score, along with confusion matrix analysis. The results showed high precision and recall values, indicating that the system effectively minimizes both false positives and false negatives. This ensures reliable detection and reduces the chances of misdiagnosis.

In addition to performance improvements, the incorporation of Explainable Artificial Intelligence

Doi:10.48047/ijiee.2026.16.2.7

(XAI) techniques such as saliency maps and Grad-CAM provided visual insights into the model's decision-making process. These visualizations highlighted the regions of MRI images that contributed most to the predictions, thereby increasing transparency and trust among medical professionals.

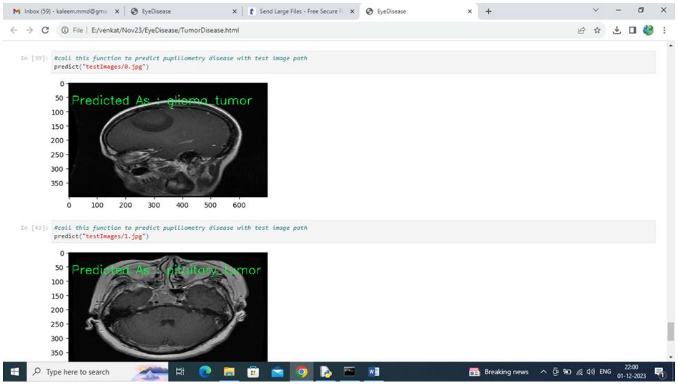

Fig:7.2: Output 2

Overall, the outcomes of this research demonstrate that the proposed system is highly effective, accurate, and clinically relevant. It reduces the workload on radiologists by automating the detection process, improves diagnostic consistency, and supports early identification of brain tumors. The combination of deep learning, multi-sequence MRI analysis, and explainable AI makes the system a powerful tool for modern healthcare applications and has the potential to enhance patient outcomes significantly.

VIII.CONCLUSION

This research presents an effective and intelligent system for **brain cancer detection using multi-sequence MRI with deep segmentation models**. The study demonstrates that integrating advanced deep learning techniques with multi-modal MRI data significantly improves the accuracy and reliability of tumor detection compared to traditional methods. The use of Convolutional Neural Networks (CNNs) and pre-trained models enables automatic feature extraction and robust classification, achieving high performance in identifying different types of brain tumors.

The incorporation of multi-sequence MRI data, including T1, T2, and FLAIR images, enhances the system's ability to capture diverse tumor characteristics, leading to more precise detection and segmentation. The experimental results confirm that deep learning models outperform conventional machine learning algorithms such as SVM, KNN, and Random Forest in terms of accuracy and efficiency.

Furthermore, the integration of Explainable Artificial Intelligence (XAI) techniques, such as saliency maps and Grad-CAM, improves the interpretability of the model. This transparency allows medical professionals to understand the reasoning behind predictions, thereby increasing trust and facilitating better clinical decision-making.

Overall, the proposed system successfully addresses the limitations of existing methods by providing an automated, accurate, and interpretable solution for brain tumor detection. It reduces the workload on radiologists, minimizes diagnostic errors, and supports early detection, which is critical for effective treatment planning. With further clinical validation and real-world implementation, this approach has the potential to significantly enhance healthcare outcomes and contribute to the advancement of AI-driven medical diagnostics.

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Doi:10.48047/ijiee.2026.16.2.7