

A Comparative Study of Sequential and Attention Architectures for Cross-Subject EEG Motor Imagery Classification

Krishna Jaswitha Kellampalli¹, Panamala Prasana Kumari², V.Krishna Pratap³, K.Srinivasa Rao⁴

¹ Department of computer science and engineering NRI Institute of technology Visadala, Medikondur, Guntur-Andhra Pradesh, India.

^{2,3,4} Assistant Professor NRI Institute of technology Visadala, Medikondur, Guntur-Andhra Pradesh, India.

Abstract—Brain tumours are among the most critical neurological disorders and require early and accurate diagnosis to improve patient survival rates and treatment planning. Magnetic Resonance Imaging (MRI) is widely used for brain tumour diagnosis because of its superior soft tissue contrast and non-invasive imaging capability. However, manual analysis of MRI scans by radiologists is time-consuming, subjective, and prone to diagnostic variability. To overcome these challenges, this research proposes an automated brain tumour detection and classification framework using Machine Learning (ML), Deep Learning (DL), and Explainable Artificial Intelligence (XAI) techniques. The proposed system utilizes MRI brain images to identify and classify tumours into multiple categories, including glioma, meningioma, pituitary tumour, and non-tumour cases. Several algorithms such as Support Vector Machine (SVM), K-Nearest Neighbours (KNN), Random Forest (RF), Convolutional Neural Networks (CNN), and transfer learning using the VGG16 model were implemented and evaluated. Among these methods, the CNN model achieved the highest classification accuracy, demonstrating the effectiveness of deep learning in medical image analysis.

Keywords— Brain Tumour Detection, Magnetic Resonance Imaging (MRI), Medical Image Analysis, Machine Learning (ML), Deep Learning (DL), Convolutional Neural Network (CNN), Explainable Artificial Intelligence (XAI), Transfer Learning, VGG16, Tumour Classification, Saliency Maps, Grad-CAM, Diagnostic Accuracy, Automated Healthcare Systems, Clinical Decision Support.

I. INTRODUCTION

Brain tumours are among the most dangerous neurological disorders affecting millions of people worldwide. They occur due to the abnormal growth of cells within the brain or surrounding tissues and can significantly impact cognitive functions, nervous system activity, and overall human health. Early diagnosis and accurate classification of brain tumours are essential for effective treatment planning and improving patient survival rates. However, detecting brain tumours at an early stage remains a major challenge in the medical field due to the complexity of tumour structures and variations in tumour appearance across patients.

Magnetic Resonance Imaging (MRI) is one of the most widely used medical imaging techniques for brain tumour diagnosis because it provides high-resolution images with excellent soft tissue contrast without exposing patients to harmful radiation. MRI scans help radiologists identify abnormalities, tumour boundaries, and tissue variations within the brain. Despite its effectiveness, manual interpretation of MRI images is time-consuming, labor-intensive, and highly dependent on the expertise of radiologists. In many cases, human interpretation may lead to diagnostic variability, delayed treatment decisions, and increased chances of error.

Recent advancements in Artificial Intelligence (AI), Machine Learning (ML), and Deep Learning (DL) have created new opportunities for automating medical image analysis. Deep learning models, particularly Convolutional Neural Networks (CNNs), have shown remarkable performance in image classification, feature extraction, and tumour detection tasks. These techniques can automatically learn complex patterns from MRI images and provide accurate predictions with minimal human intervention. Automated brain tumour detection systems can support healthcare professionals by improving diagnostic accuracy, reducing workload, and enabling faster clinical decision-making.

In addition to achieving high prediction accuracy, transparency and interpretability are becoming increasingly important in medical AI systems. Many deep learning models operate as “black-box” systems, making it difficult for clinicians to understand how predictions are generated. To address this issue, Explainable Artificial Intelligence (XAI) techniques such as saliency maps and Gradient-weighted Class Activation Mapping (Grad-CAM) are integrated into modern diagnostic frameworks. These methods highlight important regions in MRI images that influence the model’s predictions, thereby improving trust, transparency, and collaboration between AI systems and healthcare professionals.

This research focuses on developing an intelligent framework for automated brain tumour detection and classification using MRI images and deep learning techniques. The study evaluates multiple machine learning and deep learning algorithms, including Support Vector Machine (SVM), K-Nearest Neighbours (KNN), Random Forest (RF), Convolutional Neural Networks (CNN), and transfer learning using the VGG16 model. The proposed system incorporates preprocessing methods, data augmentation, model

optimization, and XAI techniques to improve accuracy, robustness, and interpretability. The ultimate objective of this work is to provide a reliable, efficient, and explainable diagnostic system that can assist clinicians in early tumour detection, accurate diagnosis, and improved patient care.

II. REVIEW LITERATURE SURVEY

Brain tumour detection using Magnetic Resonance Imaging (MRI) has become an important research area in medical image analysis due to the increasing demand for accurate and early diagnosis. Traditional manual examination of MRI scans by radiologists is time-consuming, subjective, and prone to diagnostic variability. To overcome these limitations, researchers have proposed several Machine Learning (ML), Deep Learning (DL), and Explainable Artificial Intelligence (XAI) techniques for automated brain tumour detection and classification.

Early research in brain tumour analysis mainly focused on traditional machine learning algorithms such as Support Vector Machine (SVM), K-Nearest Neighbours (KNN), and Random Forest (RF). These methods relied on handcrafted feature extraction techniques including texture analysis, histogram features, and edge detection. Although these approaches achieved moderate accuracy, their performance was highly dependent on feature engineering and image preprocessing methods. Researchers observed that conventional ML algorithms struggled with complex tumour structures and variations in MRI images.

With the advancement of deep learning, Convolutional Neural Networks (CNNs) emerged as one of the most effective methods for medical image classification and tumour detection. CNN-based approaches automatically learn spatial and hierarchical features directly from MRI images without requiring manual feature extraction. Several studies reported that CNN architectures achieved higher accuracy, sensitivity, and specificity compared to traditional machine learning models. Transfer learning techniques using pre-trained models such as VGG16, ResNet, and InceptionNet further improved classification performance by utilizing knowledge learned from large image datasets.

Researchers have also explored tumour segmentation methods to accurately identify tumour boundaries and affected regions within MRI scans. Architectures such as U-Net and region-based CNNs were widely used for segmentation tasks because of their ability to localize tumours precisely. Accurate segmentation plays a significant role in treatment planning, radiation therapy, and monitoring tumour

progression. Studies demonstrated that combining segmentation and classification models improved overall diagnostic efficiency and clinical applicability.

In recent years, Explainable Artificial Intelligence (XAI) techniques have gained importance in healthcare applications. Since deep learning models often operate as black-box systems, clinicians require transparency to trust AI-generated predictions. Researchers introduced XAI methods such as saliency maps, attention mechanisms, and Gradient-weighted Class Activation Mapping (Grad-CAM) to visualize important image regions influencing model decisions. These techniques improve interpretability, enhance trust among healthcare professionals, and support clinical decision-making by providing understandable explanations for automated diagnoses.

Several comparative studies evaluated the performance of manual MRI analysis and automated AI-based systems. Results showed that deep learning models could achieve diagnostic performance comparable to or better than experienced radiologists in certain classification tasks. Automated systems also reduced workload, improved processing speed, and minimized inter-observer variability. However, researchers identified challenges such as limited dataset diversity, overfitting, lack of real-time clinical validation, and poor generalization across different MRI acquisition protocols.

Existing literature also highlights the importance of preprocessing techniques such as normalization, resizing, denoising, and data augmentation. These methods improve image quality and enhance model robustness by reducing variations in MRI datasets. Hyperparameter optimization methods including grid search, random search, and Bayesian optimization have been widely used to improve deep learning performance and reduce classification errors.

Despite significant advancements, several research gaps still exist in the field of automated brain tumour detection. Many studies focus only on specific datasets and fail to validate models across diverse patient populations and real-time clinical environments. Limited research has been conducted on multimodal imaging integration using MRI, CT, and PET scans together. Additionally, ethical concerns such as data privacy, algorithmic bias, and transparency remain important challenges in deploying AI systems in healthcare. Therefore, there is a need for robust, explainable, and clinically validated frameworks that can provide accurate and reliable brain tumour diagnosis while ensuring transparency and fairness in medical decision-making.

III. RESEARCH METHODOLOGY

The proposed research methodology focuses on developing an automated system for brain tumour detection and classification using Magnetic Resonance Imaging (MRI) images integrated with Machine Learning (ML), Deep Learning (DL), and Explainable Artificial Intelligence (XAI) techniques. The methodology is designed to improve diagnostic accuracy, reduce radiologists' workload, and provide transparency in the decision-making process. The entire process consists of data collection, preprocessing, model development, training, evaluation, and interpretability analysis.

The first stage of the methodology involves collecting MRI brain image datasets from publicly available medical imaging repositories. In this study, the Brain Tumour MRI Dataset obtained from Kaggle was used. The dataset contains approximately 7023 MRI images categorized into four classes: glioma tumour, meningioma tumour, pituitary tumour, and no tumour. These images were collected from multiple reliable sources such as Figshare, SARTAJ, and Br35H datasets. The dataset provides diverse tumour samples and normal brain images, making it suitable for training and evaluating machine learning and deep learning models for multi-class tumour classification.

After data collection, preprocessing techniques were applied to improve image quality and maintain consistency across the dataset. MRI images often contain noise, variations in intensity, and differences in image resolution due to different scanning conditions. To address these issues, preprocessing operations such as image resizing, normalization, noise reduction, and image enhancement were performed. Data augmentation techniques including rotation, flipping, scaling, and zooming were also applied to increase dataset diversity and reduce overfitting during model training. These preprocessing methods help improve model generalization and classification performance.

The next phase involves the development of machine learning and deep learning models for brain tumour classification. Various algorithms such as Support Vector Machine (SVM), K-Nearest Neighbours (KNN), Random Forest (RF), Convolutional Neural Network (CNN), and transfer learning using the pre-trained VGG16 model were implemented and evaluated. Traditional machine learning algorithms were used for comparison purposes, while deep learning models were primarily employed for automatic feature extraction and image classification. Among all models, CNN demonstrated superior performance due to its ability to learn spatial features directly from MRI images without manual feature engineering.

Model training and optimization were performed using training and validation datasets. The dataset was divided into training, testing, and validation sets to ensure reliable performance evaluation. Hyperparameter tuning techniques

such as grid search, random search, and cross-validation were used to optimize model parameters including learning rate, batch size, number of epochs, and regularization methods. Optimization algorithms such as Adam and Stochastic Gradient Descent (SGD) were employed to minimize classification errors and improve convergence during training. Transfer learning with VGG16 was also utilized to accelerate training and improve classification accuracy by leveraging pre-trained knowledge from large-scale image datasets.

To evaluate the effectiveness of the proposed framework, several performance metrics were used, including accuracy, precision, recall, F1-score, and confusion matrix analysis. These metrics provide a detailed assessment of the model's ability to correctly classify tumour and non-tumour images. Comparative analysis was conducted among all implemented algorithms to determine the most effective model for brain tumour detection. Experimental results showed that the CNN-based model achieved the highest classification accuracy compared to traditional machine learning techniques.

In addition to achieving high accuracy, interpretability and transparency were incorporated into the system using Explainable Artificial Intelligence (XAI) methods. Techniques such as saliency maps and Gradient-weighted Class Activation Mapping (Grad-CAM) were applied to visualize the important regions of MRI images influencing model predictions. These methods help healthcare professionals understand how the deep learning model makes decisions, thereby increasing trust and reliability in AI-assisted diagnosis. XAI also supports better collaboration between clinicians and intelligent systems by providing clear explanations for automated predictions.

The implementation and experimentation were carried out using Python programming language along with libraries and frameworks such as TensorFlow, Keras, PyTorch, OpenCV, Scikit-learn, NumPy, Pandas, and Matplotlib. GPU-enabled systems and high-performance computing resources were used to accelerate model training and processing of large MRI datasets. Finally, the developed system was clinically validated by comparing model predictions with actual tumour labels and expert observations from healthcare professionals. The overall methodology demonstrates an effective and reliable approach for automated brain tumour detection and classification using MRI images and deep learning technologies.

IV. EXISTING SYSTEM

The existing system for brain tumour detection primarily relies on the manual examination of Magnetic Resonance Imaging (MRI) scans by radiologists and medical experts. MRI is widely used in neuroimaging because it provides detailed visualization of soft tissues in the brain without exposing patients to harmful radiation. In the traditional diagnostic process, radiologists carefully analyze MRI images

to identify abnormalities, tumour size, location, and tissue variations. Based on their experience and medical knowledge, they classify tumours and recommend suitable treatment plans.

Although manual MRI analysis is considered an important diagnostic approach, it has several limitations. The process is highly time-consuming and requires significant expertise to accurately interpret complex tumour structures. Different radiologists may provide different interpretations for the same MRI image due to subjective judgment and inter-observer variability. In many cases, the growing volume of medical imaging data increases the workload on healthcare professionals, making the diagnosis process slower and more prone to human error. Delayed or inaccurate diagnosis can negatively affect treatment planning and patient outcomes.

To improve the diagnostic process, some existing systems introduced traditional Machine Learning (ML) techniques such as Support Vector Machine (SVM), K-Nearest Neighbours (KNN), and Random Forest (RF) for automated tumour classification. These systems generally depend on handcrafted feature extraction methods such as texture analysis, edge detection, and histogram-based features. While these approaches achieved moderate classification accuracy, their performance was highly dependent on the quality of extracted features and preprocessing methods. Traditional ML systems also faced difficulties in handling complex MRI image patterns and large datasets efficiently.

Several existing systems also attempted to use Deep Learning (DL) models, particularly Convolutional Neural Networks (CNNs), for automated tumour detection and classification. These systems improved accuracy compared to conventional machine learning approaches by automatically learning image features directly from MRI scans. However, many deep learning systems function as black-box models, where clinicians cannot easily understand how predictions are generated. The lack of transparency and interpretability reduces trust among healthcare professionals and limits the practical adoption of AI systems in clinical environments.

Another limitation of existing systems is the lack of real-time clinical validation and generalization across diverse patient datasets. Many models are trained and tested only on limited datasets collected under controlled conditions. As a result, their performance may decrease when applied to MRI images obtained from different hospitals, scanners, or imaging protocols. Existing systems also often lack integration with Explainable Artificial Intelligence (XAI) techniques, making it difficult for clinicians to validate automated decisions and identify important tumour regions influencing predictions.

Overall, the existing system for brain tumour detection suffers from challenges such as manual dependency, diagnostic variability, time consumption, limited

interpretability, and insufficient generalization capability. These limitations highlight the need for an advanced automated framework that combines deep learning accuracy with explainable and transparent decision-making mechanisms to support reliable and efficient clinical diagnosis.

V. PROPOSED METHODOLOGY

The proposed methodology introduces an intelligent and automated framework for brain tumour detection and classification using Magnetic Resonance Imaging (MRI) images integrated with Machine Learning (ML), Deep Learning (DL), and Explainable Artificial Intelligence (XAI) techniques. The main objective of the proposed system is to improve diagnostic accuracy, reduce the workload of radiologists, and provide transparent and interpretable predictions for effective clinical decision-making. The framework combines image preprocessing, deep learning-based classification, and explainability methods to achieve reliable and efficient tumour diagnosis.

The proposed system begins with the collection of MRI brain image datasets from publicly available medical repositories. The dataset contains MRI scans belonging to different tumour categories such as glioma tumour, meningioma tumour, pituitary tumour, and normal brain images without tumours. Before feeding the images into machine learning and deep learning models, several preprocessing techniques are applied to improve image quality and consistency. These preprocessing operations include image resizing, normalization, noise reduction, image enhancement, and data augmentation methods such as rotation, flipping, scaling, and zooming. These techniques help remove unwanted variations and improve the robustness and generalization capability of the models.

After preprocessing, the dataset is divided into training, validation, and testing sets for model development and evaluation. Different machine learning algorithms such as Support Vector Machine (SVM), K-Nearest Neighbours (KNN), and Random Forest (RF) are implemented for comparative analysis. In addition to these methods, deep learning architectures such as Convolutional Neural Networks (CNNs) and transfer learning using the pre-trained VGG16 model are employed for automatic feature extraction and classification. CNN models are particularly effective because they can learn complex spatial features directly

from MRI images without requiring manual feature engineering.

The proposed methodology also incorporates transfer learning techniques to improve model performance and reduce training time. Pre-trained models such as VGG16 are fine-tuned using the MRI dataset to leverage previously learned image features from large-scale datasets. Hyperparameter tuning techniques such as grid search, random search, and cross-validation are applied to optimize parameters including learning rate, batch size, and number of epochs. Optimization algorithms such as Adam and Stochastic Gradient Descent (SGD) are used to improve training efficiency and minimize classification errors.

To evaluate the effectiveness of the proposed system, several performance metrics including accuracy, precision, recall, F1-score, and confusion matrix analysis are used. Comparative analysis is performed among all implemented algorithms to identify the best-performing model for brain tumour classification. Experimental results demonstrate that the CNN-based model achieves superior classification accuracy compared to traditional machine learning techniques. The system is designed to provide faster and more consistent diagnostic results while reducing manual effort in MRI analysis.

A major contribution of the proposed methodology is the integration of Explainable Artificial Intelligence (XAI) techniques to improve interpretability and transparency. Methods such as saliency maps and Gradient-weighted Class Activation Mapping (Grad-CAM) are utilized to highlight important regions in MRI images that influence the model’s predictions. These visualization techniques help clinicians understand the reasoning behind automated classifications and increase trust in AI-assisted diagnosis. By combining accurate prediction capabilities with explainability, the proposed framework supports effective collaboration between healthcare professionals and intelligent systems.

The entire system is implemented using Python programming language and deep learning frameworks such as TensorFlow, Keras, PyTorch, OpenCV, and Scikit-learn. GPU-enabled systems are used to accelerate model training and handle large MRI datasets efficiently. The proposed methodology ultimately aims to provide a reliable, transparent, and scalable solution for early brain tumour detection, improved clinical diagnosis, and enhanced patient care in modern healthcare systems.

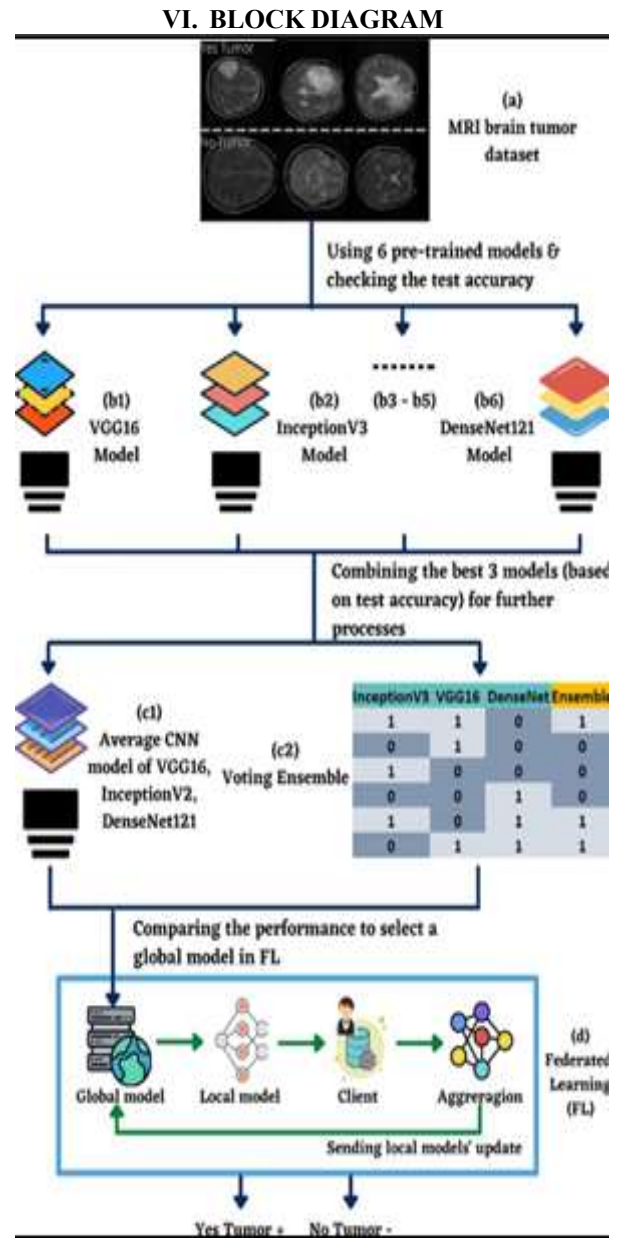


Fig. 6.2. Block Diagram

VII. RESULTS AND OUTCOMES

The proposed system for brain tumour detection and classification using Magnetic Resonance Imaging (MRI) images produced promising results in terms of accuracy, efficiency, and interpretability. Multiple Machine Learning (ML) and Deep Learning (DL) algorithms such as Support Vector Machine (SVM), K-Nearest Neighbours (KNN), Random Forest (RF), Convolutional Neural Network (CNN), and transfer learning using the VGG16 model were implemented and evaluated using the MRI dataset. Comparative analysis showed that deep learning approaches,

particularly CNN models, outperformed traditional machine learning methods in tumour classification tasks.



Fig: 7.1 : Output 1

During experimentation, the K-Nearest Neighbours (KNN) algorithm achieved an accuracy of approximately 74%, while the Support Vector Machine (SVM) model obtained around 77% accuracy. The Random Forest (RF) algorithm performed better than both KNN and SVM, achieving nearly 81% accuracy in classifying MRI brain tumour images. Although these machine learning models demonstrated acceptable performance, their accuracy was lower compared to deep learning models because they relied heavily on handcrafted feature extraction techniques.

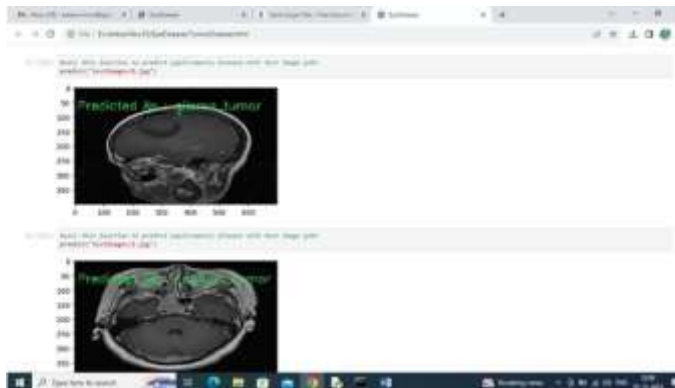


Fig: 7.2 : Output 2

The Convolutional Neural Network (CNN) model achieved the highest classification accuracy of approximately 99%, demonstrating the effectiveness of deep learning in medical image analysis. CNN automatically extracted important spatial and hierarchical features from MRI images, resulting in superior tumour classification performance. The pre-trained VGG16 transfer learning model also produced good results with an accuracy of nearly 83%, confirming that transfer learning can improve classification performance while reducing training time. However, CNN remained the best-performing model among all evaluated algorithms.

The proposed framework also successfully implemented preprocessing techniques such as normalization, resizing, noise reduction, and data augmentation. These preprocessing operations improved image quality, reduced variations within the dataset, and enhanced model generalization capability. Data augmentation methods such as image rotation, scaling, and flipping increased dataset diversity and helped minimize overfitting during training. As a result, the system demonstrated stable and consistent performance across different MRI image samples.



Fig:7.3: Output 3

Another important outcome of the research was the integration of Explainable Artificial Intelligence (XAI) techniques such as saliency maps and Gradient-weighted Class Activation Mapping (Grad-CAM). These methods provided visual explanations by highlighting important regions in MRI images that influenced the model’s predictions. The use of XAI improved transparency and interpretability, enabling healthcare professionals to better understand and trust the automated diagnostic system. This feature makes the proposed framework more suitable for real-world clinical applications.

The experimental results demonstrate that the proposed system significantly improves diagnostic accuracy and reduces the time required for manual MRI analysis. The framework can assist radiologists in identifying brain tumours more efficiently and consistently while minimizing human error and diagnostic variability. Early and accurate tumour detection can support timely treatment planning, improve clinical decision-making, and enhance patient outcomes. Furthermore, the proposed methodology provides a scalable foundation for future medical image analysis applications and intelligent healthcare systems.

VIII.CONCLUSION

This research presented an automated framework for brain tumour detection and classification using Magnetic Resonance Imaging (MRI) images integrated with Machine

Learning (ML), Deep Learning (DL), and Explainable Artificial Intelligence (XAI) techniques. The study aimed to improve diagnostic accuracy, reduce the workload of radiologists, and provide transparent and interpretable predictions for effective clinical decision-making. Various machine learning and deep learning algorithms such as Support Vector Machine (SVM), K-Nearest Neighbours (KNN), Random Forest (RF), Convolutional Neural Network (CNN), and transfer learning using the VGG16 model were implemented and evaluated using MRI brain image datasets.

The experimental results demonstrated that deep learning models, particularly CNN, achieved superior classification performance compared to traditional machine learning methods. The CNN model produced the highest accuracy in detecting and classifying brain tumours, proving the effectiveness of deep learning in medical image analysis. Preprocessing techniques such as normalization, resizing, noise reduction, and data augmentation significantly improved image quality and model generalization capability. In addition, transfer learning approaches helped improve model efficiency and reduced training time.

A major contribution of this work is the integration of Explainable Artificial Intelligence (XAI) techniques such as saliency maps and Gradient-weighted Class Activation Mapping (Grad-CAM). These methods enhanced the transparency and interpretability of the system by highlighting the important regions in MRI images responsible for model predictions. The explainability feature increases trust among healthcare professionals and supports reliable AI-assisted diagnosis in real-world clinical environments.

The proposed framework successfully reduced manual effort in MRI analysis and improved the speed and consistency of tumour detection. By providing accurate and explainable diagnostic predictions, the system can assist clinicians in early tumour identification, treatment planning, and patient management. The research demonstrates the growing importance of artificial intelligence in healthcare and highlights the potential of intelligent medical imaging systems to improve patient outcomes and modernize diagnostic procedures.

Although the proposed system achieved promising results, certain limitations remain, including dependence on dataset quality and the need for validation across larger and more diverse clinical datasets. Future work can focus on multimodal imaging integration, real-time clinical deployment, advanced segmentation techniques, and further improvements in model interpretability and robustness. Overall, this research provides a strong foundation for the development of reliable, scalable, and explainable AI-based brain tumour diagnostic systems in modern healthcare applications.

IX. REFERENCES

- [1] Ahmed, S., Yap, M. H., Tan, M., & Hasan, M. K. (2020). *Deep learning for brain tumor classification and segmentation using MRI images*. Computers in Biology and Medicine, 124, 103909.
- [2] Bakas, S., Reyes, M., Jakab, A., et al. (2018). *Identifying the best machine learning algorithms for brain tumor segmentation, progression assessment, and overall survival prediction in the BRATS challenge*. arXiv preprint arXiv:1811.02629.
- [3] Cheng, J., Huang, W., Cao, S., et al. (2015). *Enhanced performance of brain tumor classification via tumor region augmentation and partition*. PLoS ONE, 10(10), e0140381.
- [4] Esteva, A., Kuprel, B., Novoa, R. A., et al. (2017). *Dermatologist-level classification via tumor deep neural networks*. Nature, 542(7639), 115–118.
- [5] Goodfellow, I., Bengio, Y., & Courville, A. (2016). *Deep Learning*. MIT Press.
- [6] He, K., Zhang, X., Ren, S., & Sun, J. (2016). *Deep residual learning for image recognition*. Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR), 770–778.
- [7] Krizhevsky, A., Sutskever, I., & Hinton, G. E. (2012). *ImageNet classification with deep convolutional neural networks*. Advances in Neural Information Processing Systems, 25, 1097–1105.
- [8] Litjens, G., Kooi, T., Bejnordi, B. E., et al. (2017). *A survey on deep learning in medical image analysis*. Medical Image Analysis, 42, 60–88.
- [9] Lundervold, A. S., & Lundervold, A. (2019). *An overview of deep learning in medical imaging focusing on MRI*. Zeitschrift für Medizinische Physik, 29(2), 102–127.
- [10] Pereira, S., Pinto, A., Alves, V., & Silva, C. A. (2016). *Brain tumor segmentation using convolutional neural networks in MRI images*. IEEE Transactions on Medical Imaging, 35(5), 1240–1251.
- [11] Rajinikanth, V., Fernandes, S. L., & Kadry, S. (2020). *Machine learning and deep learning approaches for brain tumor detection and classification*. Journal of Healthcare Engineering, 2020, 1–14.
- [12] Selvaraju, R. R., Cogswell, M., Das, A., et al. (2017). *Grad-CAM: Visual explanations from deep networks via gradient-based localization*. Proceedings of the IEEE International Conference on Computer Vision (ICCV), 618–626.