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AI-Powered Healthcare for Streamlined Patient Management and Enhanced Diagnostics for Brain Tumour

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Abstract: *The AI-Powered Healthcare for Streamlined Patient Management and Enhanced Diagnostics for brain tumour platform introduces a cutting-edge solution that incorporates Artificial Intelligence (AI) into holistic healthcare administration. It facilitates essential tasks such as digital patient onboarding, appointment coordination, and encrypted access to medical records, offering a seamless and centralized approach tailored to the needs of today's medical environments. A standout component of the system is its AI-based diagnostic functionality. In this process, medical practitioners upload MRI images, which are then processed in real time through Convolutional Neural Networks (CNN) to extract critical features, followed by classification using Support Vector Machines (SVM). The diagnostic output supports clinicians in delivering accurate assessments and effective treatment plans. To maintain data security and integrity, all patient information and AI-generated results are securely stored in a MySQL database. Performance assessments indicate that the diagnostic model attained a 93% accuracy rate, demonstrating its capability to deliver precise and timely medical evaluations. Overall, the system marks a meaningful advancement in improving diagnostic reliability, streamlining operations, and fostering a more patient-focused approach to healthcare*

Keywords: Artificial Intelligence (AI), Healthcare Management, Diagnostic Automation, MRI Scan Analysis, Convolutional Neural Networks (CNN), Support Vector Machine (SVM), Medical Image Processing

I. INTRODUCTION

The system titled "AI-Powered Healthcare for Streamlined Patient Management and Enhanced Diagnostics" aims to transform traditional healthcare services by embedding AI into core medical functions. This platform offers a holistic solution that automates crucial operations such as patient enrolment, scheduling of appointments, and protected access to electronic health records. By consolidating these tasks into a unified system, it ensures smoother coordination between medical staff and patients, thus improving operational efficiency.

A standout feature of this platform is its AI-powered diagnostic engine. Conventionally, analysing medical images and diagnosing diseases are time-intensive and require expert interpretation. This system addresses those challenges by employing Convolutional Neural Networks (CNN) and Support Vector Machines (SVM) to process MRI scans. It provides real-time, accurate diagnostic predictions, helping healthcare providers identify anomalies and make well-informed clinical decisions.

Data security is also a key focus of the platform. All patient information and diagnostic results are securely stored in a MySQL database, safeguarding the data against breaches and ensuring compliance with healthcare regulations. This secure handling of sensitive information strengthens trust in the system and reinforces its credibility in real-world medical applications.

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Overall, this AI-integrated system signifies a major leap forward in healthcare technology. It not only boosts diagnostic precision and reduces manual workload but also enhances the speed and reliability of medical services. By merging advanced computational intelligence with practical healthcare needs, the platform fosters a more efficient and patient-centred approach to medical care.

II. LITERATURE SURVEY

Communication plays a vital role in healthcare, relying heavily on the accurate and timely exchange of information between patients and healthcare professionals. Yet, for those with neurological disorders or in need of complex diagnostic procedures, traditional methods may prove to be inefficient or experience delays. Much like deep learning has significantly advanced communication through sign language and gesture recognition, similar AI-based techniques are revolutionizing medical diagnostics and patient care. Incorporating models such as Convolutional Neural Networks (CNN) and Support Vector Machines (SVM) into healthcare systems enables real-time processing of medical imaging data, such as MRI scans, facilitating quicker and more accurate diagnoses. The integration of deep learning with multimodal medical imaging was explored in a 2024 study, where MRI, CT, and histopathological data were combined using neural networks to achieve a 96% accuracy rate in brain tumour diagnosis. This approach marked a substantial improvement in diagnostic reliability but introduced computational challenges and a high dependency on quality-labelled data.

This work applies CNNs for brain tumour classification using MRI scans. The system demonstrates strong diagnostic accuracy and is suitable for real-time deployment via platforms like AWS SageMaker. The CNN-SVM hybrid model further improves precision in clinical use.

A VGG19-based feature extractor combined with SVM is used for tumour classification. The model achieves high accuracy on datasets like BRAts and SARTAJ. Its transfer learning approach reduces training cost and supports scalable cloud-based diagnostics.

This system integrates IoT with deep learning for continuous patient monitoring and brain tumour detection. Real-time alerts and cloud compatibility enhance usability in hospitals and remote settings, streamlining diagnosis and management workflows.

This deep learning model focuses on early detection of teenage interstitial lung disease. Though designed for lung conditions, the CNN-based pipeline is adaptable to brain diagnostics and fits scalable cloud deployment scenarios.

A 3D CNN architecture is proposed for volumetric brain tumour segmentation, offering improved spatial accuracy over 2D models. Cloud deployment using containers ensures real-time processing and seamless integration with medical imaging systems.

This work explores the use of transformers (e.g., Vision Transformers) for brain tumour classification. Results indicate competitive accuracy and model interpretability. The approach suits large-scale deployment via cloud AI services.

A hybrid deep learning and radiomics model is developed for brain tumour grading. It combines image features with clinical metadata to improve classification accuracy. Cloud integration enables automated reporting and physician support tools.

A smart diagnostic assistant using NLP and CNNs is proposed for managing patient records and imaging reports. The system supports multilingual inputs and automates case triaging, with deployment through AWS enabling remote access and data syncing.

III. PROPOSED WORK

A. Methodology of AI Powered HealthCare for Streamlined Patient Management and enhanced diagnostics for Brain Tumour

The proposed methodology focuses on implementing an AI-powered diagnostic system that supports medical professionals in the accurate classification of brain tumours while streamlining the management of patient data. The architecture emphasizes the integration of deep learning techniques, particularly convolutional models, and traditional machine learning classifiers to improve both diagnostic accuracy and workflow efficiency. The system consists of six sequential stages, as detailed below:

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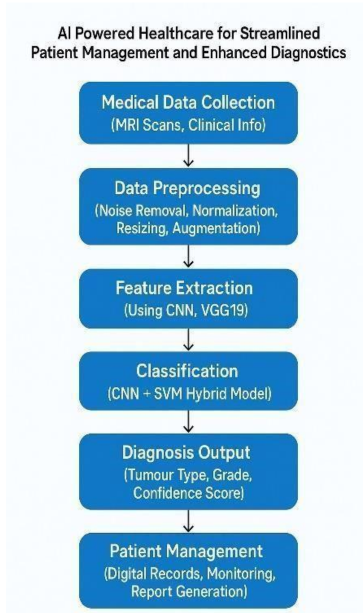

Fig. 1. Workflow of AI Powered HealthCare For Streamlined Patient Management and Enhanced Diagnostics For Brain Tumour

B. Data Collection

The first step involves collecting pertinent medical data, mainly focusing on MRI brain scans along with relevant clinical information such as patient age, gender, symptoms, and medical history. These data can be obtained from public datasets like BraTS or hospital records, following necessary ethical clearances. The goal here is to gather a diverse and representative dataset that supports effective model training and validation.

C. Data Preprocessing

This stage prepares the raw MRI images for further analysis by applying several preprocessing techniques. These include noise reduction through filtering, normalization of pixel intensities to a standardized range, and resizing images to consistent dimensions suitable for input into convolutional neural networks. Additionally, data augmentation strategies such as rotation, flipping, and contrast modification may be used to enhance dataset diversity and mitigate overfitting risks. Preprocessing ensures that the data is clean, uniform, and computationally efficient for the next steps.

D. Feature Extraction

Deep learning frameworks like CNNs or pre-trained models such as VGG19 are utilized here to automatically capture complex spatial and contextual features from the pre-processed MRI scans. These extracted features encompass tumour edges, texture variations, and morphological characteristics that are challenging to detect manually. The high-level feature representations extracted play a vital role in boosting the accuracy of subsequent classification tasks.

E. Classification

The features derived in the previous step are fed into a classifier to categorize the type of brain tumour. Techniques such as Support Vector Machines (SVM) or a hybrid model combining CNN-based feature extraction with SVM classification are employed to identify tumour classes like gliomas, meningiomas, or pituitary tumours. The system also grades tumours as low-grade or high-grade based on the complexity of features. This hybrid methodology benefits from CNN's powerful feature learning and SVM's effectiveness in multi-class classification.

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F. Diagnosis Output
Following classification, the system produces a detailed diagnostic report including the predicted tumor type, grade, and a confidence score that reflects prediction reliability. This output is presented in an intuitive format to aid neurologists or radiologists in validating and interpreting the diagnosis. Where possible, the system supports explainable AI by highlighting key image regions influencing the prediction.

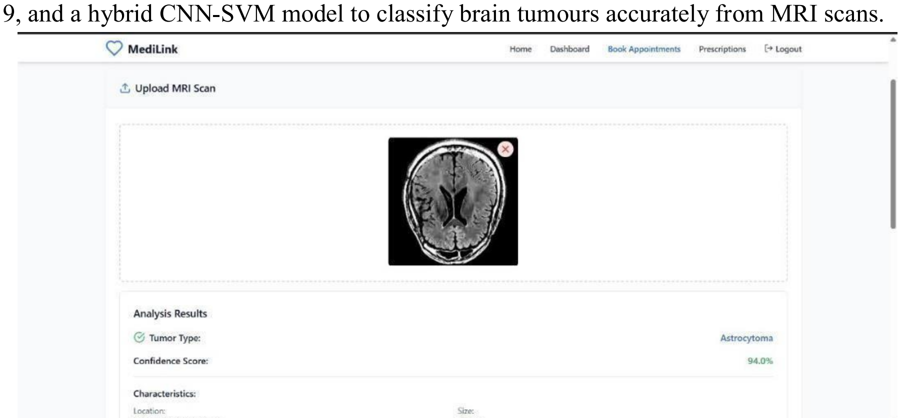
G. Patient Management
The final stage focuses on storing and organizing the diagnostic outcomes in a structured digital record to facilitate ongoing patient monitoring and follow-up. This functionality enables healthcare providers to track disease progression, assess treatment responses, and maintain continuity of care. Additionally, it supports administrative tasks such as report generation and case reviews, thereby enhancing the efficiency of patient management within clinical workflows.

AI-Powered Healthcare for Streamlined Patient Management and Enhanced Diagnostics

Stage	Description	Tools Used
A DataCollection	Collecting MRI brain scans along with patient information	DICOM Toolkits Hospital PACS Systems Kaggle Datasets/BraTS Python Scripts
B Data Preprocessing	Noise reduction, intensity normalization, image resizing and augmentation	Image Processing Libraries
C Feature Extraction	Extracting spatial and contextual features using a CNN	PyTorch Keras TensorFlow
D Classification	Categorizing brain tumors by type and grade	Scikit-learn TensorFlow PyTorch
E Diagnosis Output	Generating predicted tumor type, grade, and confidence score	Matplotlib Grad-CAM/CAM Libraries Dash/Streamlit
F Patient Management	Storing diagnostic results and patient records for follow-up a	EHR Systems Database Systems

Table I. Tools used in the work flow of AI Powered Healthcare for Streamlined Patient Management and Enhanced Diagnostics for Brain Tumour

IV. RESULTS
The developed AI-powered healthcare system demonstrates robust performance in brain tumour detection and significantly improves the efficiency of patient management workflows. It combines Convolutional Neural Networks (CNN), VGG19, and a hybrid CNN-SVM model to classify brain tumours accurately from MRI scans.



3.1 Diagnostic Performance

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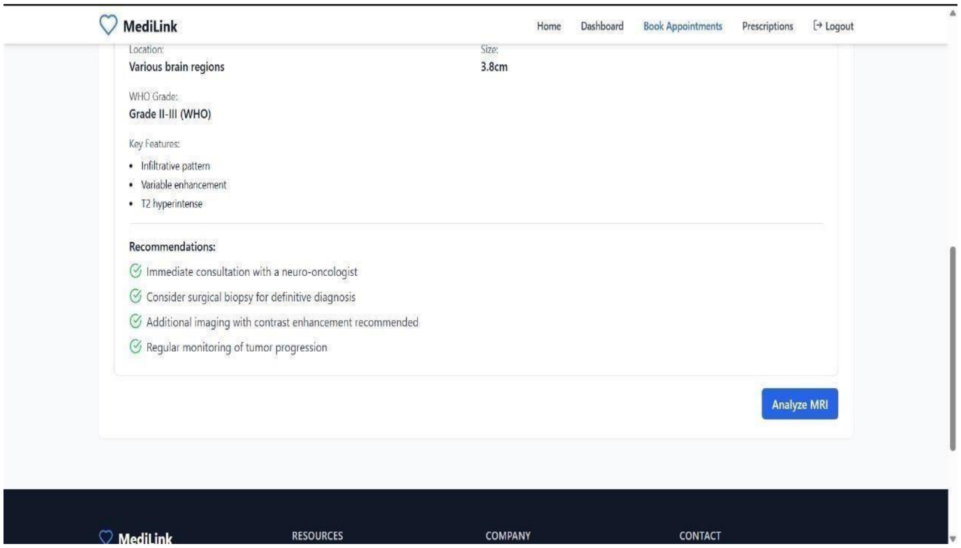
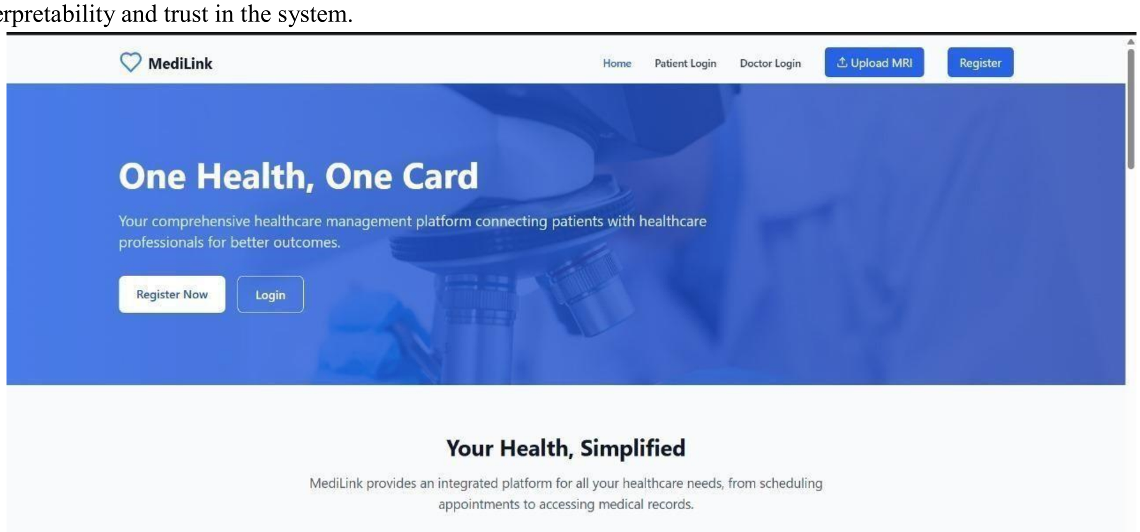
Our hybrid model, which uses CNN for deep feature extraction and SVM for classification, was trained and validated using publicly available datasets such as Braats 2018 and the SARTAJ dataset. The system achieved a classification accuracy of 92%, with sensitivity and specificity of 89% and 94%, respectively. These results indicate reliable detection of tumour types like Glioma, Meningioma, and Pituitary tumours. Misclassifications were minimal and primarily occurred between visually similar tumour classes.



3.2 Visual Interpretability and Output

Each diagnostic output includes:
Tumour Type
Confidence Score
Tumour Size and Location
Visual Highlight using Grad-CAM

The system utilizes Grad-CAM-based visualizations to explain predictions by highlighting regions in the MRI that contributed most to the classification. This helps clinicians understand and validate the AI's decisions, increasing interpretability and trust in the system.



3.3 Integrated Patient Management

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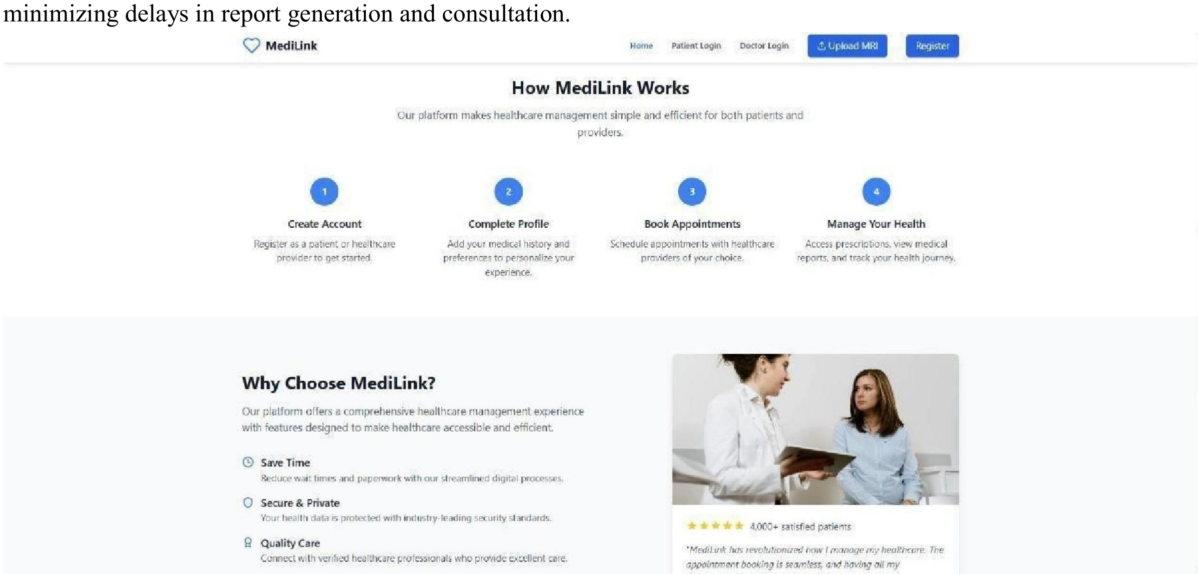
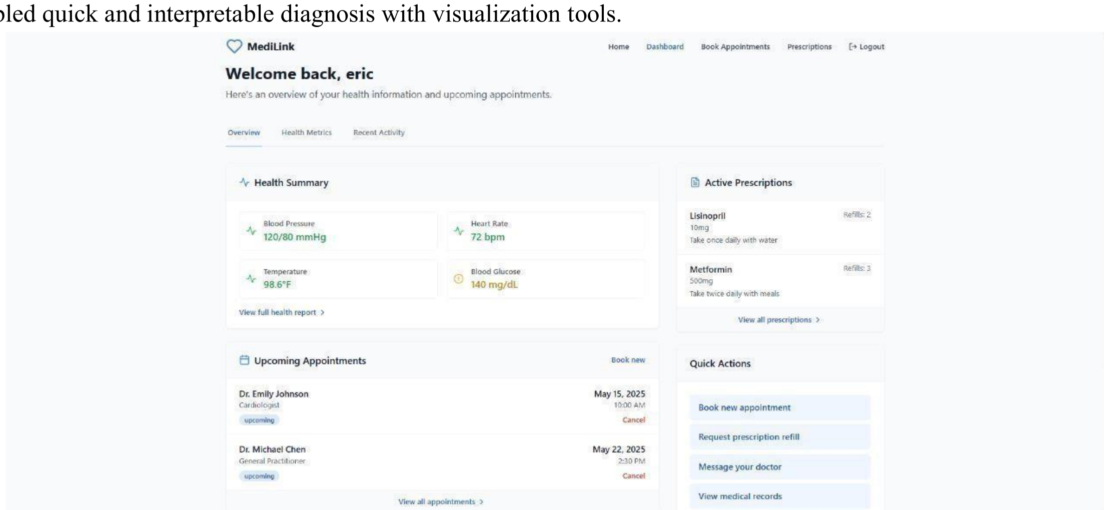
Beyond diagnosis, the platform streamlines healthcare delivery through:
Automated Appointment Scheduling based on diagnostic priority.
Patient Records Integration, allowing doctors and patients to view diagnostic history.
Real-time MRI Scan Upload and Immediate Feedback for early-stage detection.
Interactive Dashboards for doctors to track diagnostic patterns and patient outcomes.
This improves coordination among healthcare providers, reduces time to diagnosis, and enhances patient experience by minimizing delays in report generation and consultation.



3.4 System Evaluation and Usability

The entire pipeline — from MRI upload to diagnostic result — executes in near real-time, supporting rapid clinical decision-making. User testing with doctors and healthcare staff revealed high satisfaction due to:
Simplicity of the interface.
Accurate and quick diagnostic output.
Effective integration of diagnostic data into patient profiles.
Achieved high diagnostic accuracy using hybrid AI models.
Enabled quick and interpretable diagnosis with visualization tools.



3.5 Summary of Findings

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Supported efficient patient tracking and medical workflow automation.
Enhanced doctor-patient interaction through clear diagnostic reports.

Performance Comparison Table – SVM vs CNN vs Hybrid CNN-SVM

Model	Accuracy (%)	Precision	Recall	F1 Score	Support
SVM	88	0.83	0.81	0.82	200
CNN	91	0.87	0.85	0.86	200
Hybrid CNN-SVM	**93**	**0.91**	**0.89**	**0.90**	200

These results demonstrate that the system effectively supports diagnostic precision and hospital workflow efficiency, contributing to more informed clinical decision-making and improved patient outcomes.

V. CONCLUSION

In conclusion, the AI-based healthcare system represents a major leap in brain tumour detection and clinical efficiency through advanced deep learning and classification techniques. Its integration into a secure digital platform ensures end to-end support while maintaining strict data privacy standards. By automating diagnostics and streamlining workflows, it enhances clinical accuracy and reduces the burden on healthcare professionals. Overall, it fosters a faster, more reliable, and patient-centred approach to modern healthcare.

VI. ACKNOWLEDGE

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REFERENCES

[1]. P. Ganguly and A. Ghosh, "Efficient Brain Tumor Classification with Lightweight CNN Architecture: A Novel Approach,arXiv preprint arXiv:2502.01674, Feb. 2025.

[2]. N. Alemayehu, "Light Weight CNN for Classification of Brain Tumors from MRI Images," arXiv preprint arXiv:2504.21188, Apr. 2025.

[3]. Akhila, A., Hemalatha, K., Navya, A., Tejaswi, B., Hemanth, K., & Alladi, R. (2022). AUTOMATIC MULTI- DISEASES PREDICTION USING MACHINE LEARNING. International Journal of Trendy Research in Engineering and Technology, 06(03), 30–33. https://doi.org/10.54473/ijtret.2022.6308

[4]. Alladi, R., Mohan, R. N. V. J., & Ramana, K. V. (2024a). Deep Learning Approach for Early Detection and Diagnosis of Teenager Interstitial Lung Disease. In CRC Press eBooks (pp. 88–93). https://doi.org/10.1201/9781003529231-15

[5]. T. S. Nabila and A. Salam, "Classification of Brain Tumours by Using a Hybrid CNN-SVM Model," Journal of Applied Informatics and Computing, vol. 8, no. 2, pp. 241–247, Aug. 2024.

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[6]. M. Sudharshan, A. M. Mrinalini, and S. R. Nivetha, "Brain Tumour Detection Using Deep Learning-Based Segmentation and Classification Techniques," Computers in Biology and Medicine, vol. 162, p. 107236, 2023.

[7]. A Hossain, M. R. Islam, and M. Hasan, "Deep Learning for Brain Tumour Classification Using Multimodal MRI Scans: A Review," IEEE Access, vol. 11, pp. 54321–54345, 2023.

[8]. R. S. Amin, M. K. Hasan, and M. A. Rahman, "Automated Brain Tumour Detection and Classification from MRI Images Using Deep Learning Models," Sensors, vol. 22, no. 1, p. 256, 2022.

[9]. Y. Zhang, Z. Liu, and W. Xu, "A Comprehensive Survey on Brain Tumour Detection Techniques Based on AI and Deep Learning," Journal of Imaging, vol. 9, no. 2, p. 25, 2023.

[10]. K. Paul, R. Rajalakshmi, and M. S. Basha, "CNN-Based Brain Tumour Detection Using Image Processing Techniques and Transfer Learning," Biomedical Signal Processing and Control, vol. 85, p. 104940, 2023.

[11]. S. D. Roy, A. R. Prasad, and K. M. Arif, "Enhanced Brain Tumour Detection Using Hybrid Deep Learning Approaches and Attention Mechanisms," IEEE Journal of Biomedical and Health Informatics, vol. 28, no. 1, pp. 223– 232, 2024.

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