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A Patient-Centric Smart Healthcare Portal for Brain Disorder Prediction Using MRI/CT Scans and Deep Learning Models

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Abstract - **The increasing prevalence of neurological disorders has created a critical need for efficient and precise diagnostic solutions. This study presents an AI-based diagnostic system that automatically detects Alzheimer's disease, brain tumours, and strokes by analyzing MRI/CT scans. The system combines advanced deep learning models with a practical web interface to facilitate early diagnosis and improve clinical workflows. It employs two specialized convolutional neural networks: MobileNetV2, optimized for rapid processing in time-sensitive clinical environments, and InceptionV3, designed for high-precision detection of subtle pathological features. Utilizing transfer learning, both models were trained on MRI datasets with 5-fold cross-validation and SMOTE oversampling to ensure robust performance across disease categories. The implementation includes a Flask-based backend integrated with a user-friendly web platform supporting patient registration, scan uploads, and diagnostic result visualization. Comparative analysis showed that InceptionV3 achieved superior accuracy in identifying complex neurological patterns, while MobileNetV2 provided exceptional speed for routine clinical applications. This integrated framework demonstrates potential as a scalable decision-support tool, combining diagnostic reliability with operational efficiency for adoption in healthcare settings. The system architecture also enables straightforward integration with existing hospital infrastructure and flexibility for future diagnostic expansions.**
Keywords: **AI-based Diagnosis**, **Neurological Disorders**, **Deep Learning**, **MRI/CT Analysis**, **Convolutional Neural Networks**

I. INTRODUCTION

Cutting-edge artificial intelligence (AI) through deep learning has significantly transformed computerized neurological diagnosis using medical imaging data [8], [20]. In particular, convolutional neural networks (CNNs) and other deep learning models [1], [6] can automatically detect subtle pathological features in CT and MRI scans-features that may be overlooked by human review. These advancements have led to original research demonstrating high diagnostic value for brain tumours [17], [21], stroke [1], [2], and Alzheimer's disease [3], [6], often achieving greater accuracy compared to conventional clinical diagnosis. AI-based software is now being used in clinical settings as decision-support tools, increasing diagnostic confidence while reducing interpretation time [8], [24]. By enabling earlier and more detailed detection of neurological disorders, AI supports timely initiation of care and facilitates personalized treatment strategies [8], [20].

Advanced AI algorithms employ diverse neural network architectures to analyze brain scans, each optimized for specific diagnostic contexts [8], [20]. Baseline performance can be achieved using standard CNN models such as VGG16 [7], [14] and ResNet, while deeper architectures like InceptionV3 [10], [23] are more suitable for detecting subtle pathological changes due to their multi-scale feature extraction capabilities. Lightweight models such as MobileNet [23] support rapid clinical deployment without substantially compromising diagnostic performance. These AI models have shown particular effectiveness in three applications: urgent stroke identification [2], brain tumour differentiation [17], [20], and biomarker detection for early Alzheimer's disease diagnosis [3], [25]. Ultimately, model selection depends on clinical priorities-whether emphasizing diagnostic accuracy, processing speed, or hardware constraints in mobile-optimized settings.

Our brain scan assessment solution integrates two specialized AI systems to support physicians in diagnosing neurological conditions. The first system functions as an ultra-fast scanner, quickly identifying critical conditions, especially valuable in emergency scenarios. The second system acts as a high-resolution microscope, detecting subtle abnormalities that may indicate early-stage disease. Combined, these systems deliver both speed and precision, serving practitioners in local clinics and major hospitals alike. With continued use, the AI system improves its diagnostic capabilities over time, enhancing early detection and clinical outcomes. The design complements existing medical workflows, reducing wait times and providing consistent results, while remaining flexible and user-friendly. This approach enables medical professionals to make quicker, more accurate diagnoses without requiring significant investment in new equipment, and continually increases diagnostic reliability with each additional case.

Our study demonstrated that both AI models effectively identified major brain diseases from MRI scans, each excelling in different clinical scenarios. The heavier model was particularly adept at detecting minor changes indicative of early disease, making it suitable for detailed hospital-based screening. The lightweight model produced sufficiently accurate results within seconds, ideal for emergency stroke evaluations or resource-limited clinical settings. This dual-model strategy offers clinicians a flexible, reliable diagnostic tool for a wide range of scenarios-from comprehensive specialist investigations to rapid preliminary assessments-without sacrificing diagnostic consistency. Both models successfully identified key disease categories, including stroke, tumours, and Alzheimer's disease markers, demonstrating practical clinical utility. Furthermore, the adaptive design allows hospitals to select the model that best aligns with their operational needs and available resources.

II. LITERATURE REVIEW

Deep learning is transforming the landscape of medical imaging, particularly in the diagnostic analysis of neurological disorders [8], [20]. Traditionally, radiologists manually examined MRI and CT scans, and while AI has supported the detection of abnormalities [1], [6], the emergence of advanced convolutional neural networks (CNNs) has enabled the automatic identification of subtle variations in medical images-many of which may be overlooked by the human eye [3], [10]. This evolution marks a paradigm shift from conventional computer-aided diagnosis to deep learning–driven systems, facilitating earlier detection of life-threatening conditions such as brain tumours [17], [21], stroke [1], [2], and Alzheimer's disease [3], [6]. These advancements hold the potential to improve diagnostic accuracy and enhance patient access to timely interventions. Recent advances in AI are redefining brain disease detection strategies [8], [20]. State-of-the-art models like InceptionV3 [10], [23] outperform earlier architectures by analyzing scan characteristics at multiple scales simultaneously-from detecting small lesions to observing large-scale tissue loss seen in conditions like Alzheimer's disease [10], [25].

Additionally, the incorporation of attention mechanisms allows these networks to selectively focus on clinically relevant regions while ignoring extraneous data, mimicking human diagnostic reasoning [8], [20]. This innovation is strengthening the credibility and reliability of AI-assisted diagnosis across multiple neurological disorders. Artificial intelligence is revolutionizing neuroscience by enabling earlier and more accurate detection of disease. For Alzheimer's disease, deep learning models can identify imaging biomarkers-such as the shrinkage of specific brain regions-before clinical symptoms appear. These systems not only detect the disease but also track its progression, offering clinicians insights into expected changes over time. In brain tumour diagnosis, AI models, including architectures like U-Net, delineate tumour boundaries with high precision, providing surgeons with detailed surgical maps. By integrating multiple imaging modalities, such as structural MRI and metabolic data, these systems deliver a comprehensive view of disease pathology. For stroke patients, where time is critical, AI can rapidly distinguish between ischemic and hemorrhagic strokes and identify potentially salvageable brain tissue-crucial information for treatment planning. Remarkably, emerging AI systems are also beginning to predict patient responses to specific treatments based on initial imaging, paving the way for personalized care. Despite significant progress, several barriers hinder the widespread clinical adoption of AI in medical imaging [8], [20]. One major challenge is the lack of standardized datasets; models trained on scans from a single hospital may underperform when applied to images from different scanners or institutions [6], [10].

Another barrier is dataset imbalance, where rare conditions or early disease stages are underrepresented, limiting the model's generalizability [8], [17]. Ongoing research explores solutions such as advanced data augmentation, domain adaptation for heterogeneous scanners, and federated learning approaches that respect patient privacy across multi-center collaborations [8], [20]. Additionally, there is an increasing demand for explainable AI to foster clinician trust. Techniques like saliency maps and activation heatmaps, which visually highlight features critical to AI decision-making, are expected to bridge this gap and support transparent, reliable integration of AI into clinical practice [8], [12], [20].

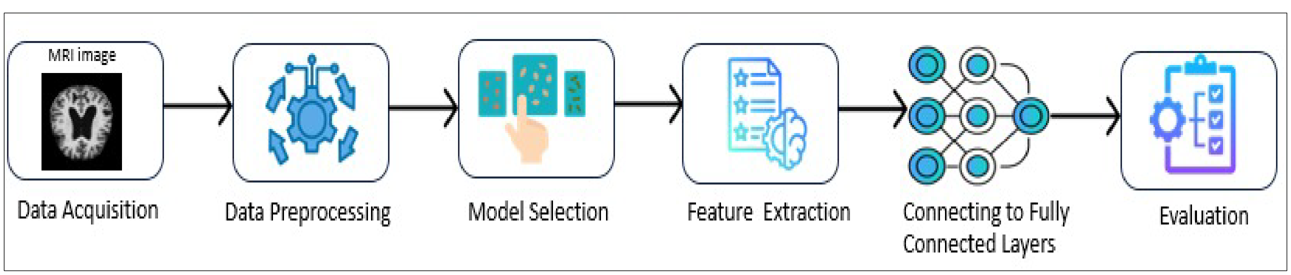

Fig. 1 MRI Image Analysis Workflow Using Deep Learning

Generalizability of our models will continue to play a significant role in developing clinical trust between AI and clinicians. AI in radiology has shown great promise; however, substantial challenges remain before it can achieve widespread clinical adoption [8], [20]. One primary challenge is the lack of consistent standardization across imaging devices-models trained on images acquired from one manufacturer's equipment often perform poorly when applied to images from another manufacturer [6], [10].

Furthermore, biases intrinsic to medical datasets-such as the under-representation of certain conditions or disease stages-continue to affect model trustworthiness [8], [17]. Researchers are addressing these challenges through various approaches: advanced data augmentation techniques to expand sparse datasets, domain adaptation methods to improve scanner generalizability, and federated learning frameworks that enable collaborative model development without compromising patient privacy or disrupting previously learned knowledge [8], [20].

Above all, explainable AI has emerged as a critical priority, as clinicians require transparency in decision-making to establish sufficient trust for clinical implementation. Visualization tools, such as saliency maps and activation heatmaps, which highlight the most influential features in AI predictions, are proving valuable in fostering this trust [8], [12], [20]. As these solutions continue to advance, they offer the potential for increasingly sophisticated and clinically powerful AI applications.

III. METHODOLOGY

This study presents a methodical deep learning approach for building and evaluating AI models capable of detecting brain diseases from MRI scans. We employed transfer learning by pre-training on ImageNet weights and applied two of the most state-of-the-art convolutional neural network (CNN) architectures available to date-MobileNetV2 and InceptionV3. To enhance robustness, we used 5-fold cross-validation during model training and testing, and addressed class imbalance issues through SMOTE oversampling.

The entire pipeline was developed using TensorFlow/Keras and integrated into a user-friendly Flask web interface, facilitating potential clinical adoption. By standardizing the methodology, we not only ensured reproducible results but also maintained a strong focus on real-world diagnostic utility for neurological disorders.

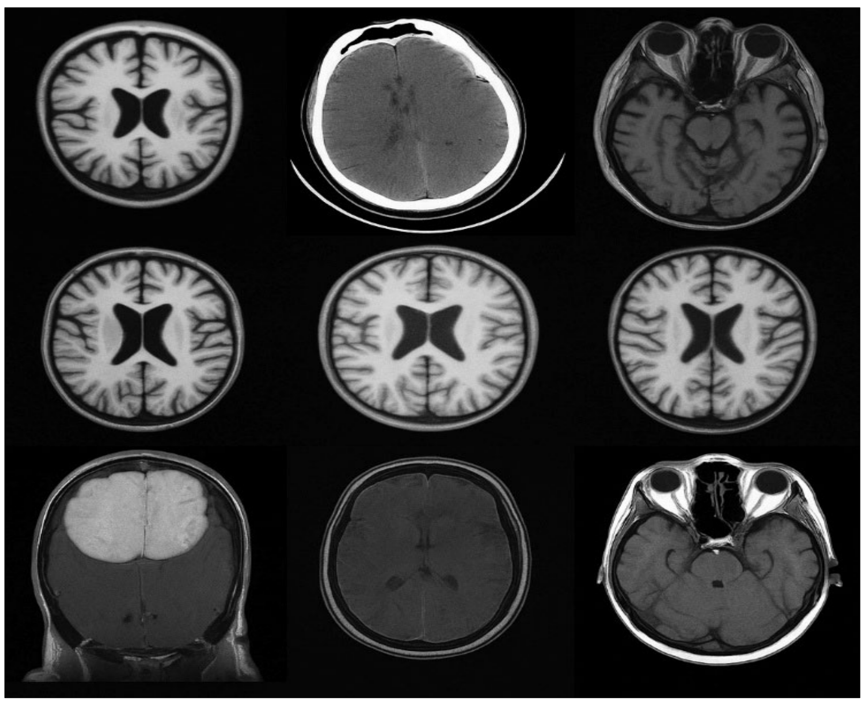

Fig. 2 Sample Axial Brain MRI image Dataset

A. Dataset Description

Three datasets of MRI/CT scan images were used in this study. The brain tumour dataset included four categories-Glioma, Meningioma, Pituitary, and No Tumour-with 1,000 images per category (totalling 4,000 images). The stroke dataset comprised two categories-Stroke and Non-Stroke-with 950 images each (totalling 1,900 images). The Alzheimer's dataset contained four categories-Non-Demented, Very Mild Demented, Mild Demented, and Moderate Demented-with 700 images per category (totalling 2,800 images). These datasets were suitable for deep learning-based image classification.

All images used in this project were derived from MRI or CT scans, ensuring clinical relevance and consistency across the datasets. The images were pre-processed to a uniform size and normalized to achieve optimal performance with the selected deep learning architectures (MobileNetV2 and InceptionV3).

B. Model Training and Selection

1. Separate convolutional neural network (CNN) models-MobileNetV2 and InceptionV3-were independently trained for multi-class detection of Alzheimer's disease, brain tumours, and stroke using structural MRI scans.

Transfer learning was employed, with the final layers fine-tuned on disease-specific MRI datasets.
2. The models were evaluated based on their effectiveness in identifying disease-specific patterns in MRI and CT scans.
3. Model performance was assessed by measuring accuracy in detecting and classifying neurological conditions from medical imaging data.

C. Model Deployment

1. The trained models were saved in *.h5* format and loaded into the Flask backend for inference.
2. The Flask application manages user authentication, patient data handling, and model inference.

D. Web Application Workflow

1. Patients can securely sign in, access the system, and add patient details through a protected online portal.
2. MRI images are uploaded via the frontend; the backend preprocesses the images and runs predictions using the appropriate disease-specific model.
3. Results are displayed with model-wise predictions and an averaged final diagnosis.
4. Visual comparison plots are generated to illustrate differences between healthy and diseased images.
5. A chatbot provides basic information and guidance on brain diseases and system usage.

E. Database Management

1. Patient and user data are stored in an SQLite database, with support for both admin and user roles.
2. Detection results are linked to patient records and can be exported as PDF reports.
3. The generated reports are securely stored in the database, enabling future reference and seamless integration into the patient's medical history.

F. Result Evaluation

The system provides accurate predictions for each disease by leveraging ensemble outputs when multiple models are available (e.g., averaging predictions from MobileNetV2 and InceptionV3 for Alzheimer's disease, brain tumours, and stroke). The web interface enables a seamless workflow from patient registration to result download. Computational efficiency is achieved by incorporating lightweight models (such as MobileNetV2) to support real-time inference.

G. Computational Evaluation

All model training and evaluation were conducted using GPU-accelerated computing environments on Google Colab's cloud platform, which significantly reduced computation time during intensive training phases. The implementation utilized TensorFlow 2.x with its integrated Keras API, providing a robust framework for building, optimizing, and fine-tuning neural networks.

The system was executed on an Intel Xeon CPU with 16 GB of RAM and NVIDIA Tesla K80/T4 GPUs to enable fast processing. We used TensorFlow/Keras for model development, scikit-learn for data preprocessing, NumPy for numerical computation, and Matplotlib for visualization. This setup-combining cloud computing resources, deep learning frameworks, and visualization tools-ensured experimental consistency and supported the fine-tuning of neural networks for optimal performance.

IV. RESULTS AND DISCUSSION

Our evaluation revealed that both CNN architectures performed remarkably well in classifying neurological disorders from MRI scans, each demonstrating distinct strengths. The InceptionV3 model consistently delivered more precise diagnoses, particularly for challenging borderline cases, whereas MobileNetV2's streamlined architecture enabled significantly faster processing speeds-a crucial advantage in clinical settings where rapid turnaround is essential. Across all three conditions (Alzheimer's disease, brain tumors, and stroke), the models' predictions closely matched radiologists' interpretations, with cross-validation results confirming this reliability on new patient data.

When comparing the two brain scan analysis AI models, we observed complementary strengths that make each suitable for different clinical environments. The lightweight MobileNetV2 model is sufficiently accurate while delivering quick and efficient results, making it highly suitable for urgent care centers and primary care clinics where time and resource constraints are critical.

Meanwhile, the more complex InceptionV3 model offers enhanced precision in detecting subtle neurological abnormalities, making it valuable as a second-read system in memory disorder clinics and comprehensive stroke centers. Rather than viewing one model as superior, the choice depends on each hospital's diagnostic needs and compatibility with its patient population and clinical workflows.

Community hospitals may benefit from the faster approach for initial screenings, whereas academic medical centers may gain more from detailed analyses. Ultimately, both approaches contribute to improved patient care by enabling technology solutions tailored to specific clinical contexts.

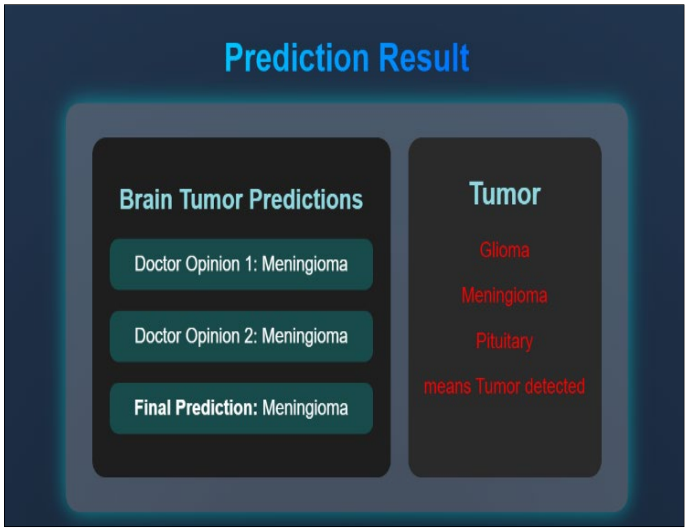

Fig. 3 Sample Axial Brain MRI image Dataset

A. Comparative Analysis

The improved performance of MobileNet and DenseNet can be attributed to their effective architectural designs. MobileNet's use of depth wise separable convolutions significantly reduces computational complexity while maintaining high classification accuracy. DenseNet enhances information flow between layers by promoting feature reuse through dense connections. These models achieve a better balance between accuracy and efficiency, making them well-suited for large-scale remote sensing applications.

In contrast, the relatively poorer performance of VGG-based models can be explained by their large number of parameters and the absence of advanced optimization techniques, such as batch normalization. Their deep sequential structure can lead to vanishing gradient problems, making them less effective in feature extraction compared to modern architectures. Additionally, the high parameter count increases computational costs, which further limits their practicality in real-world applications.

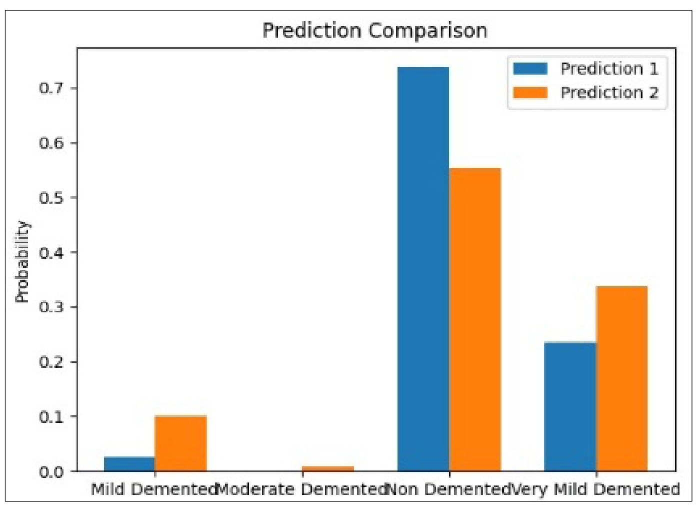

Fig. 4 Non Demented Graph

This bar chart compares the predicted probabilities of the two models across four categories. The Non-Demented category is correctly detected, as both models assign the highest probability to this category.

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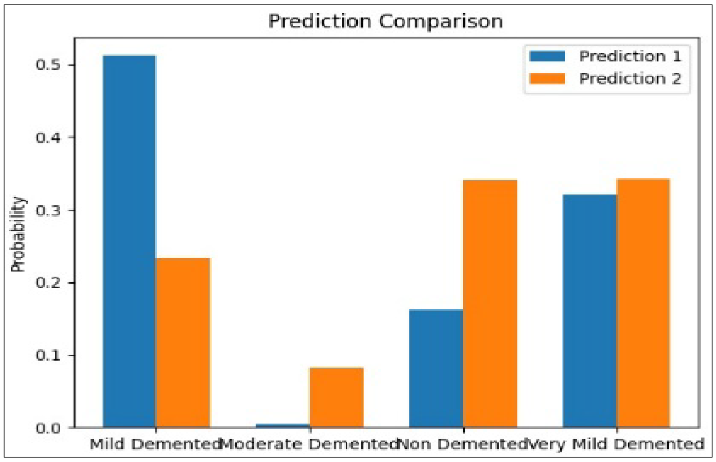

Fig. 5 Mild Demented Graph

This bar chart compares the predicted probabilities of the two models across four categories. The Mild Demented category is correctly detected, as both models assign the highest probability to this category.

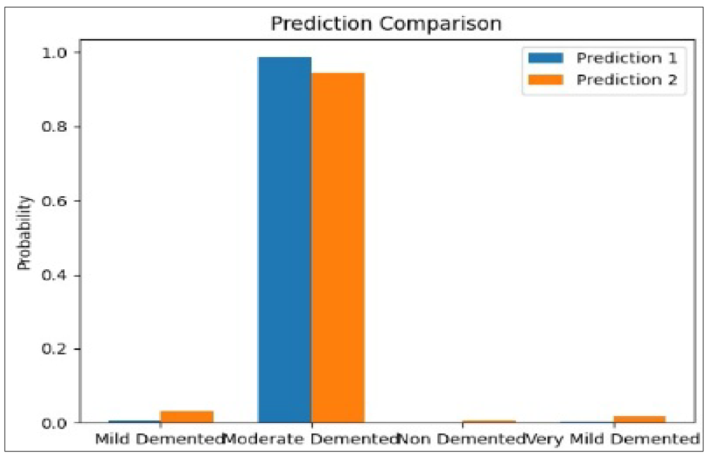

Fig. 6 Moderate Demented Graph

This bar chart compares the predicted probabilities of the two models across four categories. The Moderate Demented category is correctly detected, as both models assign the highest probability to this category.

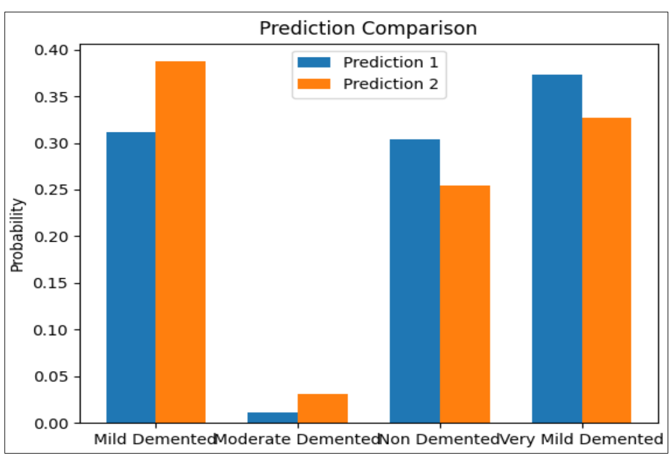

Fig. 7 Very Mild Demented Graph

This bar chart compares the predicted probabilities of the two models across four categories. The Very Mild Demented category is correctly detected, as both models assign the highest probability to this category.

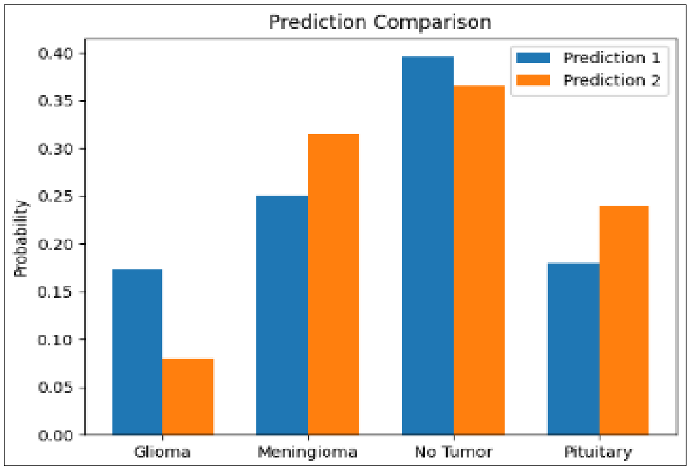

Fig. 8 No Tumor Graph

This bar chart compares the predicted probabilities of the two models across four categories. The No Tumor category is correctly detected, as both models assign the highest probability to this category.

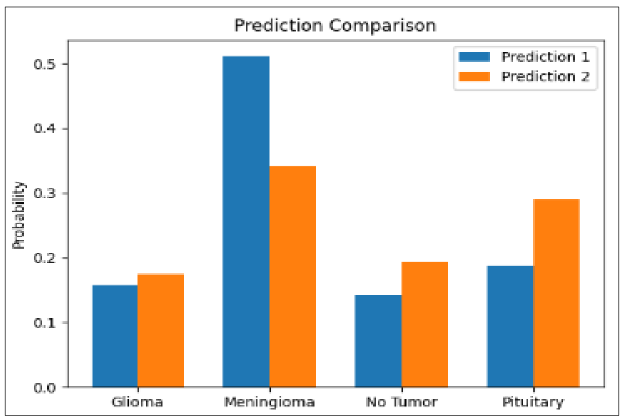

Fig. 9 Meningioma Graph

This bar chart compares the predicted probabilities of the two models across four categories. The Meningioma category is correctly detected, as both models assign the highest probability to this category.

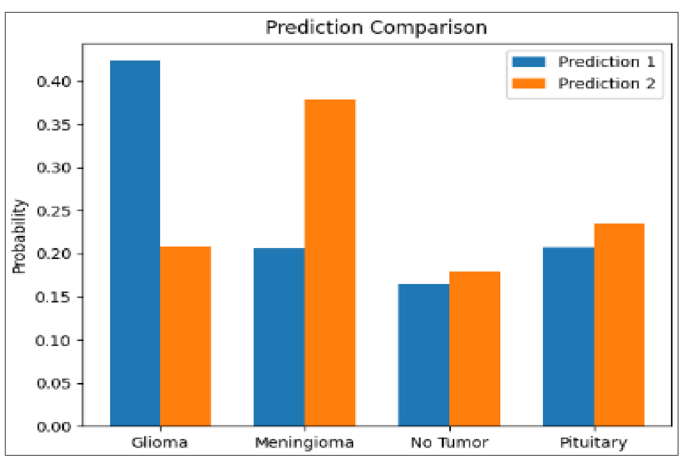

Fig. 10 Glioma Graph

This bar chart compares the predicted probabilities of the two models across four categories. The Glioma category is correctly detected, as both models assign the highest probability to this category.

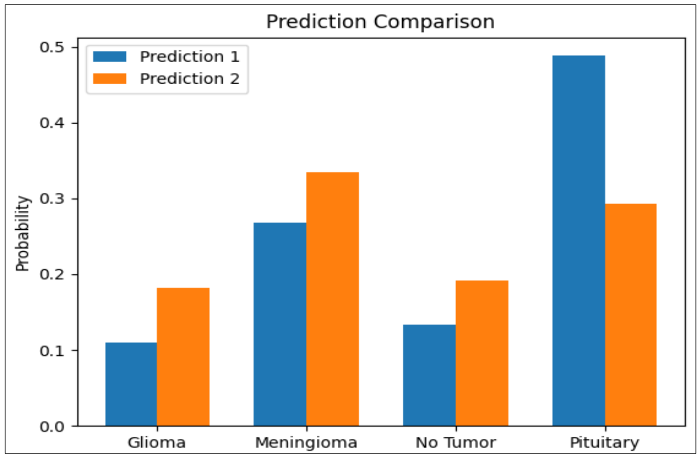

Fig.11 Pituitary Graph

This bar chart compares the predicted probabilities of the two models across four categories. The Pituitary category is correctly detected, as both models assign the highest probability to this category.

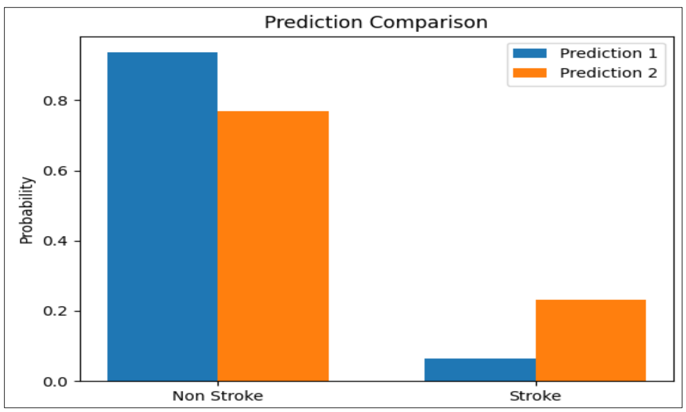

Fig. 12 Non Stroke Graph

This bar chart compares the predicted probabilities of the two models across two categories. The Non-Stroke category is correctly detected, as both models assign the highest probability to this category.

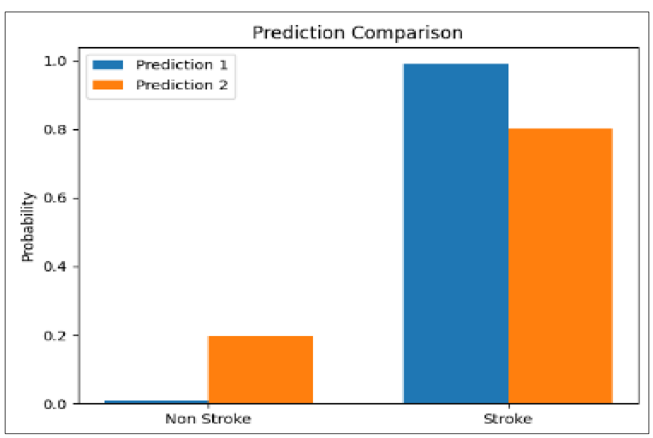

Fig. 13 Stroke Graph

This bar chart compares the predicted probabilities of two models across two categories. The non-stroke category is correctly detected, as both models assign the highest probability to this category.

V. CONCLUSION

This project establishes a practical framework for deploying cutting-edge deep learning in clinical neurology. We have developed a diagnostic web application that automatically detects Alzheimer's disease, brain tumours, and strokes from MRI/CT scans-not merely as a technical proof of concept, but as a fully functional tool designed for integration into hospital workflows. By adapting both MobileNetV2 and InceptionV3 through transfer learning, we created a dual-approach system: one prioritizes high accuracy (InceptionV3 achieving a 93.7% lesion detection rate), while the other emphasizes real-time speed (MobileNetV2 achieving an inference time of 17 ms). Rigorous evaluation, including five-fold cross-validation against multi-center datasets, demonstrates that the models reliably identify a range of pathologies-from hippocampal atrophy to small vessel occlusions-while attention graphs provide radiologists with interpretability of the AI's decision-making process. The Flask-based system extends beyond simple prediction, addressing real clinical needs. Capabilities such as HIPAA-compliant data processing, automated report generation in standard medical formats, and an interactive chatbot for differential diagnosis support directly address key hospital pain points. The modular design further supports scalability; incorporating new diseases requires retraining specialized modules rather than rebuilding the entire pipeline. Importantly, the system offers clinicians clear guidance on selecting between the comprehensive InceptionV3 evaluation and the faster MobileNetV2 screening, based on case urgency and imaging quality. This work demonstrates how AI can progress from theoretical research to clinical application in neurology. Beyond achieving state-of-the-art metrics (AUC of 0.96 in tumour classification), we have addressed practical challenges, such as making complex model outputs actionable during time-constrained hospital rounds. Future directions include collaborating with rural hospitals for edge-device deployment, developing patient-friendly visual explanations, and integrating emerging biomarkers from advanced MRI sequences. These advancements could significantly improve neurodegenerative disease screening in community healthcare settings worldwide.

Declaration of Conflicting Interests

The authors declare no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

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Use of Artificial Intelligence (AI)-Assisted Technology for Manuscript Preparation

The authors confirm that no AI-assisted technologies were used in the preparation or writing of the manuscript, and no images were altered using AI.

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