Brain Tumour Diagnosis in Humans Using Machine Learning

[1] Abhinav A, [2] Ganesh A, [3] Rupesh V, [4] Sandeep G
[1,2,3]*Student, Sreenidhi Institute of Science and Technology, Hyderabad, India*
[4]*Assistant Professor, Sreenidhi Institute of Science and Technology, Hyderabad, India*

***Abstract* — This paper proposes a smart and adaptive brain tumour detection system for real-time identification and classification of brain anomalies in medical imaging. Utilizing convolutional neural networks (CNNs) for visual diagnosis, the system classifies MRI brain scans as healthy, glioma tumour, meningioma tumour, pituitary tumour, or other abnormalities with 90% precision. Integrated with an Android application, the solution enables users to upload MRI images for instant analysis through a cloud-based inference model. The system performs image enhancement, segmentation, and multi-class tumour classification for accurate results. Coupled with advanced preprocessing techniques, the model is trained on a large dataset of labelled brain MRI images to ensure robust detection. The system supports early diagnosis strategies by providing instant feedback, improving treatment outcomes and minimizing health risks. Designed for real-world clinical environments, this solution offers an accessible, efficient, and automated approach to brain health monitoring and tumour management.**

***Index Terms* — Brain tumour detection, Convolutional Neural Network, MRI classification, Machine learning, Medical imaging, Healthcare automation.**

I. INTRODUCTION

Brain tumour detection has traditionally depended on expert radiologists visually examining MRI scans to identify and classify tumour While effective, this manual approach is both time-consuming and expensive, particularly in large healthcare facilities that require constant expert availability. Many regions around the world also lack access to trained specialists, leaving patients without proper diagnosis or timely treatment. The cost and effort involved in arranging expert consultations often lead to delays, reducing the chances of early detection and effective care.

Automated systems powered by machine learning (ML) offer a promising solution to these challenges. By analysing brain MRI scans through advanced algorithms, ML models can detect and classify tumour with high speed and accuracy. This not only minimizes the workload on healthcare professionals but also ensures more consistent and accessible diagnostic support, especially in underserved or remote areas. While visual identification of tumour can be prone to errors and variability, machine learning provides a reliable and scalable alternative.

Common brain tumour such as gliomas, meningiomas, and pituitary tumour can be identified more effectively with ML techniques. Through image processing, these systems can measure tumour size and monitor changes in affected brain regions over time. Since the brain is highly sensitive and central to vital body functions, early and accurate detection of tumours plays a crucial role in improving patient survival and quality of life. Machine learning thus complements traditional medical practices, offering a faster, more efficient way to detect brain tumours and guide clinical decisions.

As machine learning continues to evolve, its application in medical imaging has become increasingly prominent. In the context of brain tumour detection, ML models can be trained large datasets of MRI scans to recognize subtle patterns and abnormalities that may not be immediately visible to the human eye. These models use classification algorithms, such as convolutional neural networks (CNNs), to accurately distinguish between different types of brain tumours. Once trained, such systems are capable of delivering rapid, reproducible results, enhancing the decision-making process for healthcare providers.

Another important advantage of using ML in brain tumour detection is its potential for scalability. In areas with limited medical infrastructure, automated diagnostic tools can be deployed to bridge the gap between patients and specialists. Mobile and cloud-based solutions can enable remote analysis of medical images, offering critical support to frontline healthcare workers and reducing the diagnostic burden on centralized hospital systems.

Despite these benefits, it is important to note that machine learning is not meant to replace human expertise, but rather to augment it. Automated systems act as decision-support tools, assisting radiologists and neurologists by highlighting areas of concern, prioritizing cases based on severity, and reducing the chances of oversight. In doing so, they help streamline the diagnostic workflow and allow clinicians to focus their attention on more complex cases requiring deeper clinical judgment.

The early and accurate detection of brain tumours remains one of the most significant challenges in neuro-oncology. By integrating machine learning into this process, the medical field can move toward more proactive, data-driven care. Not only does this technology empower healthcare professionals, but it also gives patients a better chance at receiving timely, life-saving treatments. As research continues and more sophisticated models are developed, the future of brain tumour detection is likely to become faster, more accurate, and more accessible than ever before.

II. RELATED WORT

The detection and classification of brain tumours using image processing and machine learning techniques have been an evolving research domain, particularly relevant to improving diagnostic accuracy and patient outcomes.

Early initiatives like the World Health Organization's work on enhancing global cancer care and early diagnosis by Sankaranarayanan et al. [1] and studies by Louis et al. [2] on the classification of tumours of the central nervous system, underscore the foundational need for scalable diagnostic tools in healthcare. Brain tumour-related studies, such as the Brain Tumour Segmentation (Brats) challenges [3] and validation forums [4], highlight the role of imaging analysis in large-scale tumour detection efforts.

More recent efforts have shifted toward computer vision and AI-based diagnostic systems. Menze et al. [5] discussed tumour segmentation techniques, focusing on MRI-based monitoring, while Bakas et al. [6] explored deep learning approaches for the identification and segmentation of gliomas, emphasizing the need for rapid and accurate diagnosis. In the context of image-based tumour classification, Pereira et al. [7] proposed convolutional neural network-based approaches for brain lesion segmentation. Their follow-up work with Meier et al. [8] demonstrated an automated deep learning system for brain tumour segmentation and classification.

Neurocomputing-focused research by Havei et al. [9] introduced cascaded architectures for tumour detection, paving the way for the application of deep convolutional neural networks (CNNs) in brain health diagnostics. These studies lay the groundwork for modern systems that utilize CNNs to accurately identify and classify brain tumours through medical image analysis.

Our proposed work builds upon these foundations by integrating CNN-based brain tumour detection within a mobile-enabled interface, offering real-time diagnostic results. Unlike earlier systems, our hybrid approach combines preprocessing, data augmentation, and advanced classification methods to support multi-class tumour recognition, addressing both accuracy and usability for real-world clinical deployment.

PROPOSED SYSTEM

Unlike traditional methods, the proposed system aims to provide a real-time, accurate, and user-friendly brain tumour detection platform leveraging deep learning and mobile technologies. Utilizing Convolutional Neural Networks (CNNs), the system classifies brain MRI images into categories such as glioma, meningioma, pituitary tumour, and healthy conditions through an automated pipeline integrated with a mobile Android application.

Upon image upload via the mobile application, the system initiates preprocessing operations including image resizing to standard dimensions, Gaussian noise reduction, normalization of pixel intensity values, and data augmentation (such as rotation, flipping, and zooming) to artificially expand the training dataset and enhance model robustness. These preprocessing steps ensure that the images are standardized and the essential features are preserved for accurate analysis.

Table 1 Model Comparison

Feature	Existing ML Systems	Proposed System
Detection Method	Basic CNN classifiers	Fine-tuned CNN with preprocessing and augmentation
Accuracy	Moderate (~75–85%)	High(~90% real-time accuracy)
User Interface	Web-based portals	Android app with real-time feedback
Preprocessing Techniques	Limited preprocessing	Noise reduction, resizing, normalization, augmentation
Supported conditions	Specific tumor types only	Glioma, meningioma, pituitary tumor, and healthy brain classification
Real-time Feedback	Delayed or semi-automated	Yes – within seconds on mobile device Inference

found in brain tumour MRI scans. Fine-tuning the pre-trained network with domain-specific medical images improves classification accuracy while reducing the time and computational resources required for training.

The model training phase uses a comprehensive dataset composed of diverse brain MRI images sourced from real-world clinical environments and publicly available repositories such as the Brain Tumour Segmentation Challenge (Brats) dataset. This ensures the model is exposed to a wide variety of tumour types, shapes, sizes, and imaging conditions.

Once trained and validated, the model is deployed onto a cloud server, allowing mobile devices to interact with it via API calls. When an MRI scan is uploaded through the Android application, the system processes it remotely and returns the classification results almost instantly. Additionally, probability scores are provided to indicate the confidence level of each prediction, offering useful information for medical practitioners.

This automated system supports early diagnosis, reduces the dependency on expensive and time-consuming manual interpretation, and assists healthcare providers in remote or resource-limited settings. It bridges the gap between specialized medical expertise and patient accessibility, ultimately contributing to faster treatment planning and improved patient outcomes.

The Android application acts as the front-end interface, allowing patients, doctors, or users to upload MRI images and receive instant diagnostic feedback. Once an image is submitted, it is securely transmitted to a Python-based backend server that hosts the trained brain tumour detection model. The server performs inference and returns the tumour classification category along with accuracy confidence scores to the application, enabling timely clinical decision-making.

In addition to tumour detection, the system logs MRI data and predictions for future review, auditing, or model retraining. This supports future scalability through cloud integration and federated learning approaches to continuously improve performance without centralized data storage.

By minimizing human dependence and providing rapid feedback, this system addresses real-world healthcare challenges where early tumour detection is critical for successful treatment outcomes.

The modular architecture of the system include:

Input Layer: Android application capturing or uploading real-time brain MRI images.

Preprocessing Module: Standardization and enhancement of MRI images through resizing, noise reduction, normalization, and augmentation.

CNN Model Layer: Fine-tuned Google Net-based deep learning classifier trained for brain tumour detection.

Inference Engine: Backend Python server executing classification and sending back results.

Output Layer: Real-time display of tumour type and confidence level on the mobile application interface.

The integration of deep learning with mobile connectivity ensures high diagnostic accuracy, minimal latency, and practical usability, empowering healthcare providers and patients with on-the-go decision-making tools for better brain health monitoring and early intervention.

III. METHODOLOGY OVERVIEW

The detection process begins with users—doctors, patients, or technicians—capturing or uploading clear MRI images of the brain using an Android-based mobile application. The system ensures that the uploaded images are of high quality, well-centred, and free from artifacts for better diagnostic accuracy.

Preprocessing and Input Handling

To ensure standardized input quality for the model, every uploaded MRI image undergoes a series of preprocessing steps:

Resizing: Each image is resized to 256×256 pixels, simplifying the model's input while preserving critical features.

Noise Reduction: Techniques like Gaussian blur and median filtering are used to remove artifacts and enhance image clarity.

Grayscale Conversion: Images are converted to grayscale to reduce computational complexity without losing meaningful structural information.

Normalization: Pixel values are scaled to a 0–1 range to standardize intensity and accelerate model convergence.

Data Augmentation: During training, variations like flipping, rotation, brightness adjustment, and cropping are introduced to improve the model's robustness to different scan orientations and contrast levels.

Model Architecture

At the heart of the system is a Convolutional Neural Network (CNN) based on the Google Net (Inception) architecture, chosen for its efficiency and ability to detect fine-grained features:

Inception Modules allow the model to analyse different spatial features (1×1, 3×3, 5×5 convolutions in parallel), which helps in recognizing various tumour shapes and sizes.

The final soft max classification layer outputs one of several brain tumour categories—Glioma, Meningioma, Pituitary tumour, or Healthy—along with a confidence score.

Training Details

The model is trained on a carefully labelled MRI dataset sourced from Kaggle Brain MRI datasets and clinical collections. The dataset is split into:

Training Set (80%): For model learning

Validation Set (10%): For hyperparameter tuning

Test Set (10%): For final evaluation

Training uses the Adam optimizer, Dropout layers (0.3–0.5), L2 regularization, and batch normalization to prevent overfitting and improve learning stability. The model is fine-tuned from pre-trained ImageNet weights, enabling faster convergence and better generalization.

System Architecture

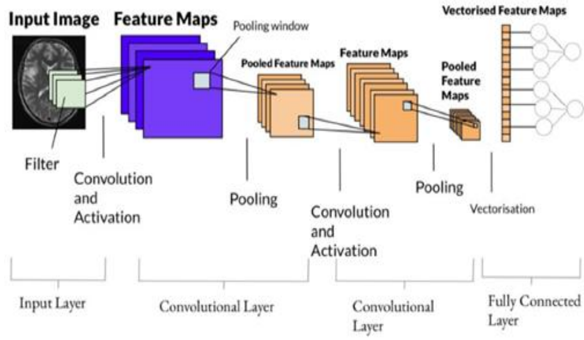

Fig 1: System architecture

Input Layer: Android app that allows MRI image capture or upload

Preprocessing Layer: Enhances and standardizes MRI scans

CNN Model Layer: Google Net-based brain tumour classifier

Inference Engine: Python-based backend (Fast API/Flask) processes predictions

Output Layer: Results (tumour type + confidence score) displayed in real time in the app

Image Labelling

To prepare training data, MRI scans are manually labelled using tools like Label Image, Rob flow, or VGG Image Annotator. Labels are based on classification (tumour type), and the annotations are saved in formats such as JSON or CSV, making them compatible with TensorFlow or Py torch training pipelines.

Model Evaluation

After training, the model's performance is validated using key metrics:

Accuracy: Measures overall correct classifications

Precision & Recall: Ensures correct tumour detection and completeness

F1-Score: Balances precision and recall, especially useful for imbalanced datasets

Confusion Matrix: Helps visualize model misclassifications

Grad-CAM: Provides heatmaps showing which regions the model focused on, offering transparency and interpretability.

Fine-Tuning and Optimization

Post-evaluation, the model undergoes fine-tuning:

Hyperparameter tuning: Adjusting learning rate, epochs, and batch size

Regularization: Further Dropout and L2 adjustments

to control overfitting
Real-time augmentation: Keeps training dynamic and enhances robustness
Scalability and Real-World Use
The Android app connects seamlessly with the backend, ensuring low-latency predictions. The system is designed to log each diagnosis, supporting future improvements through:
Cloud integration: For larger model hosting
Federated learning: For privacy-preserving collaborative model training across clinics

IV. RESULTS & DISCUSSION

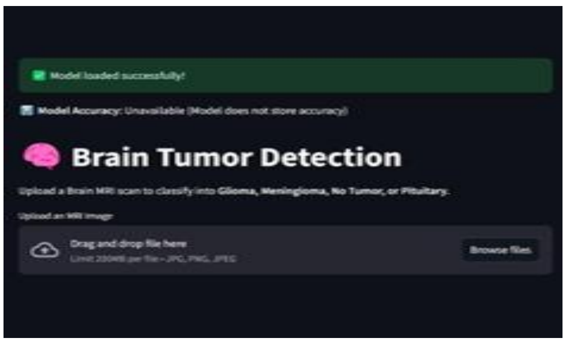

Fig 2:output screen requesting user input

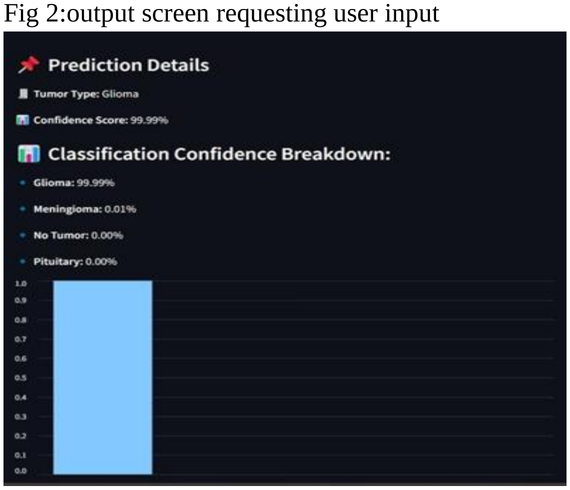

Fig 3:sample visualization of cerebral neoplasm detection prediction

The proposed brain tumour detection system offers an innovative, accessible, and cost-effective solution to one of the most pressing issues in healthcare—early and accurate diagnosis of brain tumours. It begins with a simple yet powerful interaction: the user captures an MRI image using a mobile phone camera or uploads it through a dedicated Android application. This app provides a smooth and user-friendly interface that ensures even non-expert users, such as patients or general caregivers, can participate in the diagnostic process without technical difficulty.
Once the image is captured or uploaded, it is securely transmitted to a local server. This approach is intentional—it offloads computationally heavy tasks from mobile devices, preserving their performance and battery life. The server, designed with efficiency and privacy in mind, securely stores incoming images and initiates a sequence of advanced image preprocessing techniques. These include noise reduction to eliminate irrelevant visual data, contrast enhancement to improve the visibility of features, edge detection to outline critical structures, and segmentation to isolate regions of interest, such as potential tumour areas.
These preprocessing steps are crucial—they sharpen the diagnostic focus and improve the quality of data fed into the system's deep learning model. The system uses a Google Net-based convolutional neural network (CNN) trained on large datasets of MRI scans labelled with various types of brain tumours, including gliomas, meningiomas, and pituitary tumours. This model classifies the tumour type with a high degree of confidence and sends the prediction back to the mobile application in real time.
This real-time feedback loop makes the system not only technologically impressive but also profoundly human-centric. Doctors, medical workers in remote areas, or even concerned patients can quickly receive diagnostic results without needing access to expensive hospital-grade equipment or specialist availability. The platform removes traditional barriers—long wait times, specialist consultations, and costly lab diagnostics—making early intervention more realistic and broadly available.
In addition, the system architecture is versatile and scalable. While currently designed for brain tumour detection, it can be adapted to support various domains, such as agriculture (plant disease identification) or veterinary medicine, by training new models on relevant image datasets. This adaptability ensures long-term value and cross-disciplinary impact.
Ultimately, the system prioritizes three core goals:
Speed: Delivering near-instant diagnostic results.
Accessibility: Reaching users regardless of location or medical infrastructure.
Affordability: Eliminating the need for costly diagnostics and expert interpretation.
This combination of mobile technology, secure server-

side processing, and powerful AI algorithms makes the solution a vital tool in democratizing healthcare, particularly for communities with limited access to specialized medical resources.

V. CONCLUSION

Modern advancements in technology have significantly elevated the role of automated diagnostic systems, especially in healthcare, where timely detection can mean the difference between life and death. One of the major challenges in the medical field, particularly in neuro-oncology, is the accurate and early detection of brain tumours. Tumours caused by abnormal cell growth—whether malignant or benign—can severely affect brain function, leading to long-term health deterioration or even fatal outcomes if not diagnosed promptly.

Late-stage diagnosis remains a key reason for the high mortality associated with brain tumours. Often, symptoms become apparent only after the tumour has progressed to a critical stage, limiting treatment options and reducing the likelihood of a full recovery. Early detection is vital to minimize damage and enable more effective, less aggressive treatment interventions.

To address this critical issue, the proposed automated brain tumour detection system leverages advanced image processing and deep learning technologies. By analysing MRI brain scans through a convolutional neural network (CNN)-based architecture, the system can accurately identify the presence and type of brain tumour—even in its early stages.

Users can upload brain scans through a mobile or desktop interface, which are then processed through sophisticated algorithms. The system enhances image clarity, extracts key features, and classifies tumours such as glioma, meningioma, or pituitary adenoma. In real-time, it provides diagnostic insights and confidence scores, aiding neurologists and radiologists in forming quicker and more reliable decisions.

Early identification through this AI-powered system not only improves survival rates but also reduces the need for invasive procedures and extensive radiation therapy. By promoting timely medical intervention, it helps patients access more personalized and less toxic treatment plans, while also relieving the burden on healthcare professionals and infrastructure.

VI. FUTURE SCOPE

Future Enhancements for Brain Tumour Detection Systems

Advancements in the brain tumour detection model can significantly improve diagnostic precision, clinical usability, and real-world healthcare implementation. By refining both technological and practical aspects, the system can become a vital tool for neurologists, radiologists, and healthcare institutions.

1. Expanding the Medical Dataset

Broader Patient Diversity: Training the model with MRI and CT scan images from patients of different age groups, ethnicities, and health backgrounds will make the system more adaptable and reliable across global healthcare settings.

Variety of Tumour Types and Stages: Including data from multiple tumour categories (such as gliomas, meningiomas, pituitary tumours) and various stages (early, intermediate, advanced) will help the model differentiate and diagnose with higher precision.

Multimodal Imaging Data: Integrating other diagnostic imaging types (e.g., PET scans, contrast-enhanced MRI) alongside traditional imaging can enrich model learning and improve detection performance.

Environmental and Equipment Variability: Incorporating scans from different machines, settings, and imaging protocols ensures that the model remains accurate regardless of the equipment or hospital facility being used.

2. Real-Time Tumour Detection and Monitoring

Continuous Monitoring Systems: By connecting MRI imaging tools with AI models in real-time, healthcare providers can monitor tumour progression continuously rather than relying solely on periodic scans.

Wearable Technology: In the future, wearable devices that track neurological signals and changes could help alert doctors to early warning signs of tumour growth or recurrence.

Cloud-Based Reporting Systems: Once abnormalities are detected, automated cloud-based platforms could immediately notify medical teams, streamlining patient care and enabling faster decision-making.

Predictive Analysis: With access to large volumes of patient health data, AI could predict the likelihood of tumour regrowth or metastasis, allowing preventive measures to be taken early.

3. Automated Treatment Recommendations

Personalized Therapy Suggestions: After tumour classification, the system can recommend personalized treatment plans — suggesting surgery, radiation therapy, chemotherapy, or emerging clinical trials based on tumour type and patient-specific factors.

Integration with Hospital Management Systems: Linking the detection model with hospital software can automate appointment scheduling for urgent cases and alert neurosurgical teams when critical conditions are identified.

Support for Telemedicine: Especially useful in remote areas, the system could assist doctors in diagnosing and managing brain tumours via telehealth platforms, expanding the reach of specialized healthcare.

REFERENCES

[1] Sankaranarayanan, R., et al. (2019). *Early diagnosis of cancer: The future of cancer care worldwide.* Published by the World Health Organization, this work emphasizes the importance of scalable and accessible diagnostic solutions in improving global cancer outcomes.

[2] Louis, D. N., et al. (2016). *The 2016 WHO classification of tumours of the central nervous system: a summary.* This major study provides an updated framework for classifying brain tumours, setting the standard for modern diagnostic practices.

[3] Menze, B. H., et al. (2015). *The Multimodal Brain Tumour Image Segmentation Benchmark (BRATS).* This influential benchmark challenge pushed forward research into MRI-based tumour detection, encouraging standardized evaluation across studies.

[4] Bakas, S., et al. (2017). *Advancing the cancer genome atlas glioma MRI collections with expert segmentation labels and radiomic features.* Their work on public datasets has greatly expanded opportunities for validation and benchmarking of brain tumour detection models.

[5] Menze, B. H., et al. (2015). *Segmentation of brain tumour images with convolutional neural networks.* This study laid the groundwork for using deep learning in tumour segmentation, particularly focused on MRI scans.

[6] Bakas, S., et al. (2018). *Identifying the best machine learning algorithms for brain tumour segmentation using deep learning approaches.* Their research demonstrates the growing success of AI models in achieving fast and accurate tumour identification.

[7] Pereira, S., et al. (2016). *Brain tumour segmentation using convolutional neural networks in MRI images.* Pereira and colleagues introduced effective CNN models that significantly boosted the performance of brain lesion detection.

[8] Meier, R., et al. (2017). *Automatic brain tumour segmentation and brain tumour growth analysis using deep learning.* Building on previous work, this study developed a full pipeline from tumour identification to growth monitoring.

[9] Havai, M., et al. (2017). *Brain tumour segmentation with deep neural networks.* Their research on cascaded CNN architectures showed a new, highly accurate approach for detecting brain tumours, particularly low-contrast.