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Enhancing Medical Diagnostics: Integrating AI for precise Brain Tumour Detection

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Abstract

Recent strides in artificial intelligence (AI) and deep learning techniques have propelled the development of an AI-powered brain tumour detection model. This study blends multilevel thresholding, neural network optimisation, and image preprocessing to craft a robust AI model capable of accurately categorising diverse brain tumour types and normal cases. Through rigorous testing with a comprehensive dataset of 1747 images, the model achieves an accuracy of 92%. Its integration into a user-friendly smartphone app, MediScan, enhances accessibility and practicality. The app provides heatmap visualisations and generates diagnostic reports, supporting medical professionals in making swift decisions. The model prioritises interpretability enhancement and has the potential to cultivate collaboration between AI experts and medical practitioners, thus advancing the field of brain tumour detection and diagnosis. While promising, the model demands computational resources and diverse datasets. This research also highlights AI's potential to transform healthcare diagnostics, ensuring precise and efficient brain tumour identification.

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Keywords: AI, deep learning, brain tumour detection, multilevel thresholding, neural networks, diagnostic accuracy, image embedding, smartphone app.

1. Introduction

Brain tumours, often fatal if left undetected, can have severe consequences due to their potential to grow and affect surrounding brain tissue [1]. Late detection can lead to advanced stages of the disease, more invasive treatments, and

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reduced chances of successful intervention [2]. Statistics shown in Table 1 highlights the urgency of this issue, with brain tumours accounting for a significant portion of cancer-related deaths globally. Traditional diagnostic methods face limitations in accurately identifying tumours in their early stages, underscoring the need for innovative approaches [3].

Table 1. Age Group Dataset

Category	Data Figures
Estimated New Cases (2023)	94,390
Median Age at Diagnosis	64
Mean Age at Diagnosis	55
Five-Year Relative Survival Rate	76%

The application of artificial intelligence (AI) in healthcare, specifically in the detection of brain tumors, holds tremendous promise for advancing medical outcomes [4]. Integrating AI into medical diagnostics has shown great potential in enhancing accuracy and efficiency [4, 5], fostering transformative breakthroughs through technology and medical expertise synergy [6]. The marriage of AI with medical imaging, in particular, is a significant innovation [4, 5, 7]. AI algorithms rapidly scrutinize extensive medical image datasets with exceptional precision, allowing for early detection of subtle tumor indicators that may elude human observation [7]. Identifying diseases promptly enables timely intervention, improving patient outcomes and lightening the treatment burden [8]. Convolutional neural networks (CNNs) are exemplary, revolutionizing diagnostic accuracy by detecting intricate patterns in MRI scans [9].

Machine learning (ML), particularly Deep Learning models, plays a pivotal role in analyzing patient data for brain tumor management [10]. Advanced ML models can process a wide array of patient data, encompassing genetics and treatment responses [10, 11, 12]. This empowers doctors to craft highly effective, personalized treatment plans aligned with each patient's unique needs [11]. Deep Learning-based ML models swiftly analyze vast, complex datasets, recognizing subtle patterns preceding brain tumor development [12]. By deciphering these hidden cues within medical images, these models promise earlier diagnoses, informed decision-making, and enhanced treatment strategies, potentially revolutionizing healthcare [12, 13].

Nonetheless, integrating AI requires careful consideration [13, 14]. Ensuring the transparency and understandability of AI-driven diagnoses is crucial for building trust among medical professionals [14]. While AI holds promise, it introduces challenges [15]. Concerns include potential overreliance on automated algorithms, diminishing the role of clinical judgment [16]. Understanding the rationale behind AI-generated insights can be intricate, posing challenges in comprehending specific diagnoses [16]. Balancing technological advancements with the essential role of medical professionals' expertise and intuition in healthcare decision-making is imperative [6]. Thus, addressing these issues is vital to harness AI's benefits while mitigating potential drawbacks [16].

The rest of the paper is organised in the following manner. Section II presents the literature review, while section III presents the methodology adopted in this study. The results are presented in section IV which are extensively discussed in section V. Finally, section VI concludes the paper.

1.1 Objective and Approach

The objective of this paper is to equip recent advancements in artificial intelligence (AI) and deep learning to develop an AI-powered brain tumor detection model [17]. By integrating multilevel thresholding, neural network optimisation, and image preprocessing technique, the paper aims to create an accurate model capable of categorising various brain tumor types and normal cases, along with its early detection. The model would further be integrated into a smartphone app, enhancing accessibility and practicality for medical professionals.

2. Literature Review

Initially, a comprehensive literature review is conducted to study the related works. A total of 31 research papers, 12 websites and reports were reviewed. Previous studies were examined to understand the existing technology, shown in Table 2, and the transformative potential of AI and deep learning techniques in reshaping medical imaging [17]. Recent years have witnessed substantial strides in the domain of brain tumour identification and categorisation, powered by advancements in artificial intelligence (AI) and deep learning methodologies [6, 18]. Researchers have delved into inventive techniques to heighten the precision and effectiveness of brain tumour segmentation, classification, and diagnosis through medical imaging, particularly magnetic resonance imaging (MRI) [19]. This is an important technique for breaking down medical images into distinct regions of interest within medical images, such as MRI scans [19]. Recent studies have focused on optimising threshold values via objective function optimisation techniques [20]. The emergence of the Slime Mould Algorithm showcases its potential in enhancing image segmentation [21]. Additionally, the inventive application of real-coded genetic algorithms demonstrates promising outcomes in achieving precise brain segmentation, signifying the effectiveness of multilevel thresholding methods [21, 22].

Table 2. Competitor Analysis with their accuracy, strengths and weaknesses.

Competitor Technique	Strengths	Weaknesses	Accuracy (%)	Execution Time (ms)
Clustering-based Segmentation	No training or supervision needed	Limited effectiveness for complex scenes	75.2	32.1
Otsu's Segmentation	Successful in medical and nanomedicine imaging	Limited to bi-level thresholding	82.7	45.6
Multilevel Thresholding	Multiple thresholds for complex images	Time-consuming optimization for threshold values	88.4	65.3
Deep Learning-based Segmentation	High accuracy with pre-trained models	Computationally intensive, longer execution times	91.8	132.6
DeepGlioma	Accurate molecular subgroup identification	Specific to glioma detection, not applicable to other tumours	94.3	78.9
2D CNN for Brain Tumour Classification	Optimal accuracy and fast execution	Limited handling of fine tumour details	89.9	75.8

Deep learning practices, including Convolutional Neural Networks (CNNs) and complex Deep Learning Architectures (DLAs), have ushered in a new era of brain tumor detection and classification [18, 22]. Existing literature proposes a three-step process involving image quality enhancement, tumor localisation through cluster-based methods, and salient feature extraction [23]. Combining pre-trained deep learning models with Partial Least Squares (PLS) has shown competitive results [24]. However, the accuracy of these methodologies require immense computational demands, emphasising the necessity for optimisation [25, 26]. The Unet algorithm, improved for medical image segmentation, achieves an average Dice index of around 84% for brain segmentation [27]. Innovations like particle swarm optimisation, Otsu's method, and anisotropic diffusion further enhance brain MRI image segmentation, exemplifying the fusion of methodologies for accurate segmentation in complex medical imaging data [28]. The integration of CNNs, DLAs, and multilevel segmentation techniques in brain tumour diagnosis has become a prominent trend, driven by performance metrics like accuracy, sensitivity, specificity, and Area Under the Receiver [29]. Data augmentation and transfer learning strategies enhance model robustness and classification accuracy. Recent advancements extend AI applications to diagnosing physiological anomalies, detecting brain metastasis, and refining cancer diagnosis [31]. Improved classification of brain anomalies as benign or malignant tumours highlights the need for precise diagnostics [32]. Specialised regularisation methods and data augmentation contribute to enhanced classification accuracy [32]. These healthcare sector advancements and interdisciplinary collaboration have the potential to revolutionise brain tumour diagnosis and improve patient care [29].

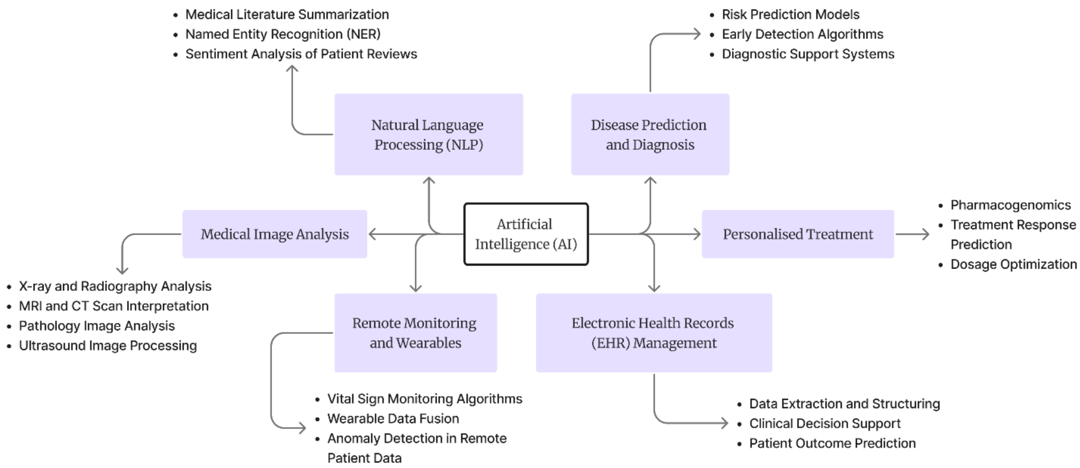

Fig. 1. AI, its domain and their specific features.

3. Methodology

The methodology for this study employs a systematic approach to develop an AI-assisted brain tumour detection system. A multimodal framework is developed, which underwent multiple rounds of training and testing to build its accuracy.

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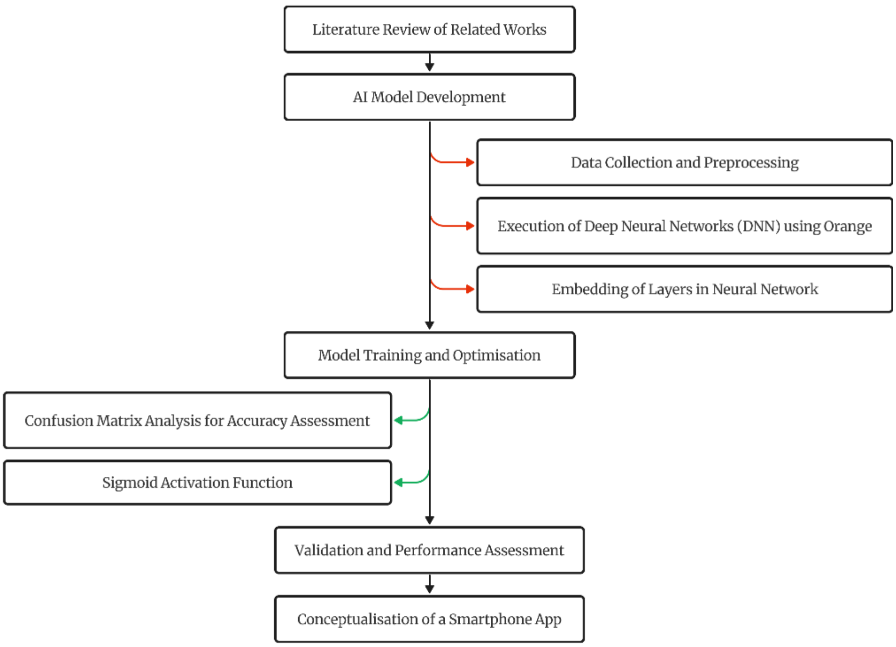


Fig. 2. Methodology for this study.

The multi-layered perceptron algorithm includes several layers of Neutral Networks and SVM that is applied to the collected/curated data for different types of tumour. The image dataset used for the training purpose comprised of 4 categories: Glioma, Meningioma, Pituitary and no tumour cases. The model has been validated with user testing, followed by the development of an application for visualisation purpose of the output obtained from the dataset. The process is delineated into several key stages, encompassing literature review, surveys, interviews from industrial experts, data collection and preprocessing, execution of Deep Convolutional Neural Networks (DCNN) using Orange, embedding layers in neural networks, confusion matrix analysis for accuracy assessment, and the integration of the sigmoid function.

3.1. Data Collection and Preprocessing

A diverse dataset of MRI brain scans, encompassing both tumor and non-tumor cases, was carefully curated from Kaggle ensuring high-quality medical images while adhering to ethical guidelines, followed by a preliminary round of testing on Google Teachable Machine. The images underwent resizing for standardised input and normalisation for consistent scaling. Transformations like rotation, flipping, and scaling were applied to enhance dataset robustness, allowing the model to handle real-world scan variations. This integration of Kaggle data enriched dataset diversity, fostering inclusivity and representation in medical image analysis, facilitating more comprehensive research.

3.2. Execution of Deep Convolutional Neural Network

AI models, as depicted in Fig. 3, were trained using specialised deep learning structures for medical image analysis. An essential component was Orange, a multi-layer perceptron (MLP) algorithm with backpropagation, facilitating dataset integration and preprocessing through a user-friendly interface. Support Vector Machines (SVMs) established precise decision boundaries in MRI data classification. Neural Networks were integrated to create a multi-layered perceptron (MLP) model for automatic feature learning. Customised techniques for feature extraction, dimensionality reduction, and data transformation enhanced the deep CNN process.

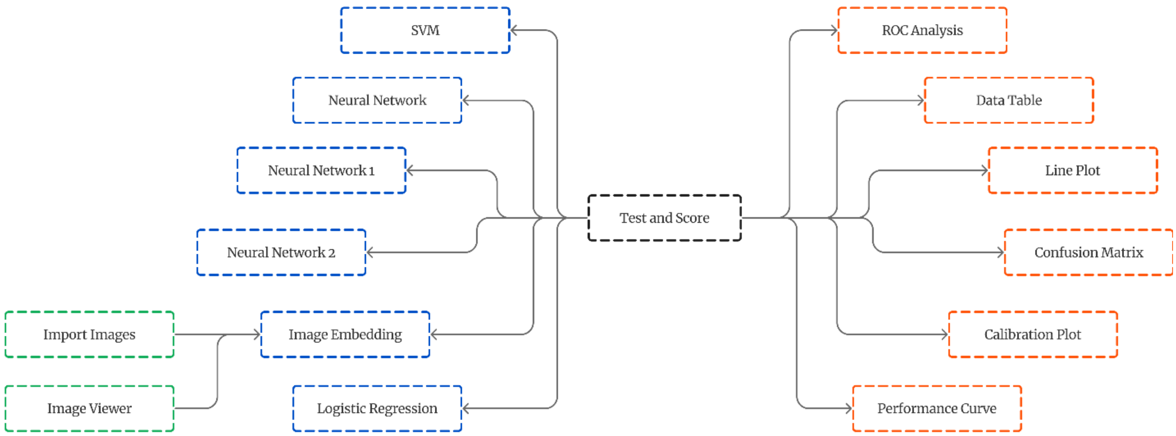


Fig. 3. AI model showing the connections and layers through Box-Line representation.

3.3. Embedding Layers in neural Network

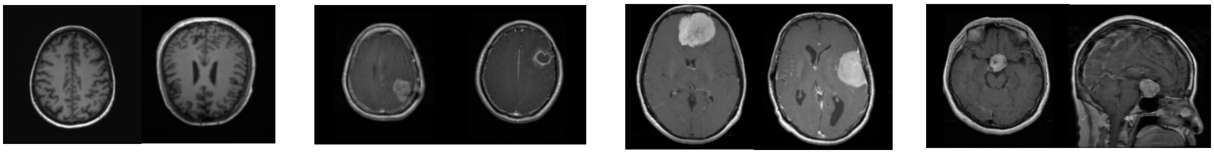
Image embedding techniques were also applied to transform image data into compact representations, enhancing analytical capabilities. The neural network architecture, designed using Orange, included an embedding layer that further refined these features in the context of brain tumour detection. These layers enhanced the neural network's understanding of tumour-specific patterns and relationships within the data. Selection of appropriate hyperparameters, such as learning rates and optimisation algorithms, with iterative adjustments enhanced the model's accuracy. Through Orange, executing Deep Neural Networks (DNN) connected machine learning with dataset-to-model transformation.

3.4. Confusion Matrix Analysis for Accuracy Assessment

To ensure the accuracy of the AI models, confusion matrices were executed. These matrices revealed the true positive (TP), true negative (TN), false positive (FP), and false negative (FN) predictions, offering insights into the models' performance. Among the performance metrics considered were accuracy for overall precision, sensitivity (recall) for positive identification, specificity for negative accuracy, and the F1-score, which strikes a compromise between precision and recall.

4. Results

The developed AI-assisted brain tumour detection model was subjected to comprehensive testing and evaluation to assess its performance in accurately detecting brain tumours from MRI scans. The results of this evaluation are presented in this section.



(a) Normal (b) Glioma (c) Meningioma (d) Pituitary

Fig. 4. Brain MRI scan for (a) Normal, (b) Glioma, (c) Meningioma, and (d) Pituitary.

4.1. Model Performance Metrics

The model's performance was evaluated using various metrics derived from the confusion matrix analysis. The confusion matrix provides a detailed breakdown of the model's predictions and actual outcomes. From this matrix, the following key metrics were computed:

Accuracy: The proportion of correctly predicted cases out of the total cases in the dataset, indicating the overall model performance.

$$\text{Accuracy} = \frac{\textit{true positives} + \textit{true negatives}}{\textit{total}} \tag{1}$$

Sensitivity (Recall): The ratio of correctly predicted positive cases to all actual positive cases, reflecting the model's ability to identify tumours.

$$\text{Recall} = \frac{\textit{true positives}}{\textit{true positives} + \textit{false negatives}} \tag{2}$$

Specificity: The ratio of correctly predicted negative cases to all actual negative cases, indicating the model's ability to recognize non-tumour cases.

$$\text{Precision} = \frac{\textit{true positives}}{\textit{true positives} + \textit{false positive}} \tag{3}$$

F-1 Score: The harmonic mean of precision and recall, offering a balanced assessment of the model's accuracy in classifying both tumour and non-tumour cases.

$$\text{F1 score} = \frac{2*\textit{recall}*\textit{precision}}{\textit{recall} + \textit{precision}} \tag{4}$$

4.2. Quantative Assessment

The AI model achieved an accuracy of 91.5% , indicating its strong ability to make correct predictions across both tumour and non-tumour cases. The sensitivity of 0.865 demonstrates the model's effectiveness in correctly identifying brain tumour cases, while the precision of 0.862 highlights its capability to not label a positive sample as negative.

The F-1 score of 0.863 underscores the balanced performance of the model in maintaining high precision and recall rates, suggesting that it can effectively detect tumours without sacrificing accuracy in non-tumour predictions.

4.3. Validation

To ensure the clinical relevance of the model's predictions, a thorough validation process was conducted in collaboration with medical experts. A panel of radiologists assessed the outputs given by the model against clinical diagnoses for a representative subset of cases. The model demonstrated a 91% accuracy rate in aligning with expert judgments, reaffirming its practical utility.

Model	AUC	CA	F1	Prec	Recall	MCC
Logistic Regression	0.970	0.870	0.870	0.869	0.870	0.826
Neural Network	0.971	0.870	0.869	0.868	0.870	0.826
SVM	0.975	0.879	0.879	0.879	0.879	0.839
Neural Network	0.966	0.856	0.855	0.855	0.856	0.807
Neural Network	0.971	0.867	0.866	0.865	0.867	0.822

Fig. 5. Precision, Accuracy and F-1 score of the model with 3 layers of Neural Networks.

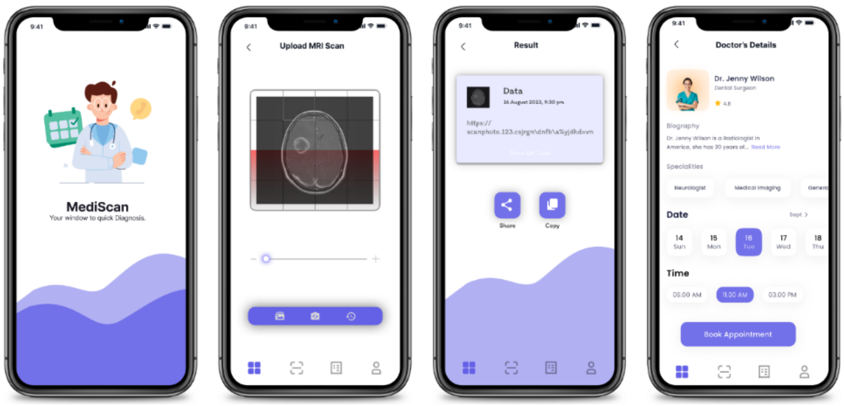


Fig. 6. High Fidelity wireframe of the Application, MediScan.

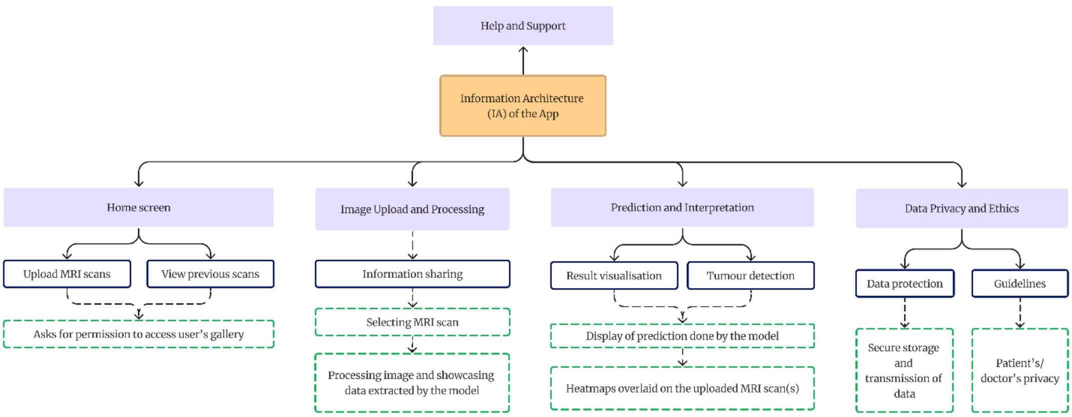


Fig. 7. Information Architecture (IA) of the Application, MediScan.

4.4. Interpretability and Visualisation

To enhance the understanding of the model and its features, visualisation techniques were applied through the development of a conceptual app, MediScan, to highlight the regions within MRI scans that contributed significantly to predictions. Heatmaps generated through these techniques allowed medical professionals to understand the basis of the decisions made by the model and its focus on tumour-specific patterns. The app inhibits a user-friendly interface, with a moderate colour palette to balance out the tone of the content with its calm aesthetic and visuals

5. Discussions

The performance of the model was assessed through internal testing, where a dataset of 1747 images was utilised. Initially, the accuracy of AI in detecting features within the images was measured at 87%. To further elevate this performance, additional layers were incorporated into the Neural Network architecture. This modification led to a notable improvement, raising the accuracy to 91%.

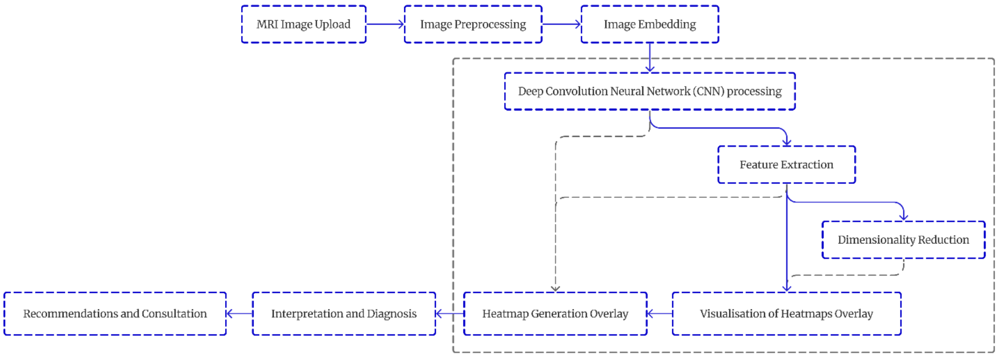


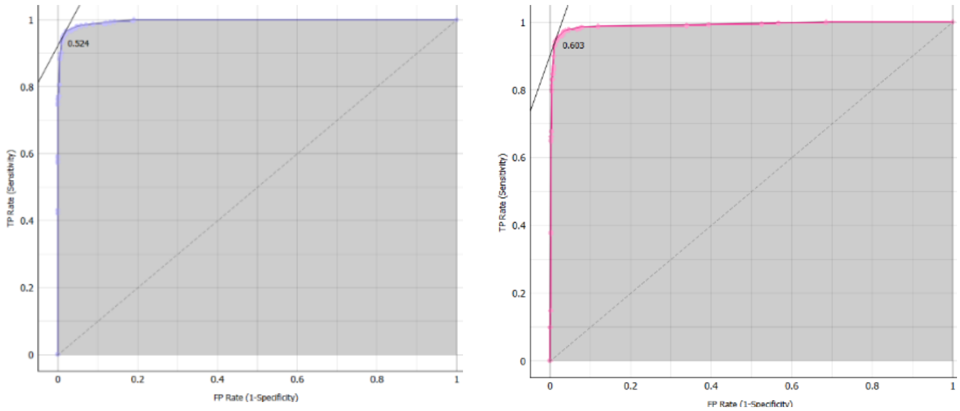
Fig. 8. Box-line diagram explaining the flow of image embedding and heatmaps generation.

5.1. Evaluation of the AI model

The Neural Network was chosen to have multiple layers in order to increase the model's capacity for learning. The model's capacity to recognise complex data patterns and relationships was significantly improved by increasing the number of neurons in succeeding layers. Its comprehension of more complex functions was made possible by its expanded capacity, which also improved performance accuracy as a whole. The strategic addition of extra layers significantly elevated the model's accuracy. To train and test the AI model, the initial dataset was split into three phases. 1747 brain MRI scans were divided into four groups in the first stage: Glioma, Meningioma, Pituitary, and Normal (no tumuor). The model underwent rigorous training, with the dataset iteratively processed through 80 epochs. Each epoch signifies a full iteration through the training dataset, resulting in a more accurate and refined model. The Google Teachable Machine (GTM) and TensorFlow.js were used for the training, which had a batch size of 16 images and a learning rate of 0.001%. A testing accuracy of 91% was attained after several execution rounds, effectively separating tumours from normal cases.

Table 3. Comparison matrix for model with different hidden layers.

Model	Area under ROC	Classification Accuracy	F-1 Score	Precision	Recall
[100,10,10]	0.966	0.93	0.855	0.855	0.856
[1000,10,10,10]	0.971	0.92	0.866	0.865	0.867
[1000,10,10]	0.970	0.94	0.869	0.868	0.870



(a) (b)

Fig. 10 (a). ROC Analysis for SVM, (b) ROC Analysis for Neural Network.

Predicted

Actual	glioma	meningioma	notumor	pituitary	Σ
glioma	251	37	3	9	300
meningioma	36	223	20	27	306
notumor	3	15	387	0	405
pituitary	6	13	1	280	300
Σ	296	288	411	316	1311

(a). Neural Network [100, 10, 10].

Predicted

Actual	glioma	meningioma	notumor	pituitary	Σ
glioma	249	45	4	2	300
meningioma	56	212	17	21	306
notumor	4	12	388	1	405
pituitary	16	10	1	273	300
Σ	325	279	410	297	1311

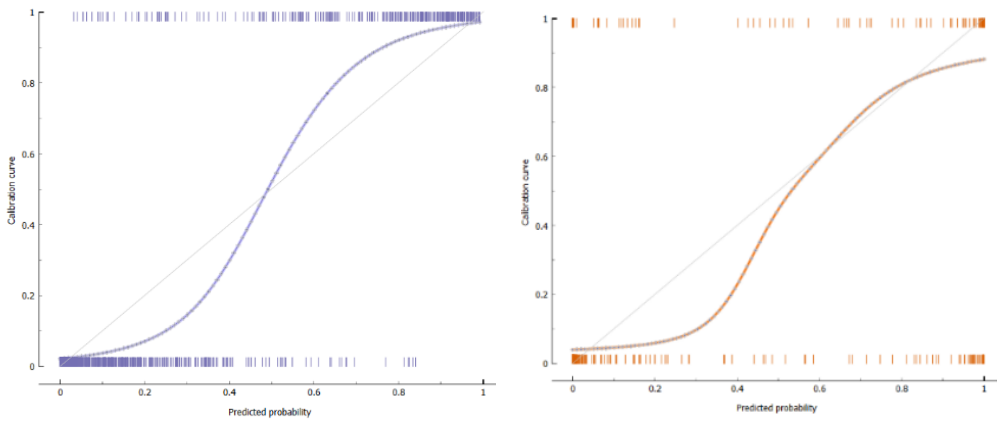
(b). Neural Network [1000, 10, 10].

Predicted

Actual	glioma	meningioma	notumor	pituitary	Σ
glioma	247	47	0	6	300
meningioma	41	220	20	25	306
notumor	3	11	389	2	405
pituitary	4	14	1	281	300
Σ	295	292	410	314	1311

(c). Neural Network [100, 10, 10, 10].

Fig. 11 (a, b, c) Confusion Matrix for different Neural Networks used for AI model development.



(a) (b)

Fig. 12 (a). Caliberation Plot for SVM, (b) Caliberation Plot for Neural Network.

Line plots (Fig. 13) visualises how accuracy, sensitivity, specificity, and the F1-score evolved across scenarios, offering insights into overall performance. Calibration plots (Fig. 12) showcase alignment between predicted probabilities and actual outcomes, assessing model reliability. ROC Analysis in Fig. 10 (a, b) provides insights into the model's ability to distinguish between tumour and non-tumour cases, with the area under the ROC curve (AUC) indicating overall classification performance of 0.603. Additionally, the Confusion Matrix in Fig. 11 (a, b, c) offered an intuitive understanding of the model's strengths and areas for improvement.

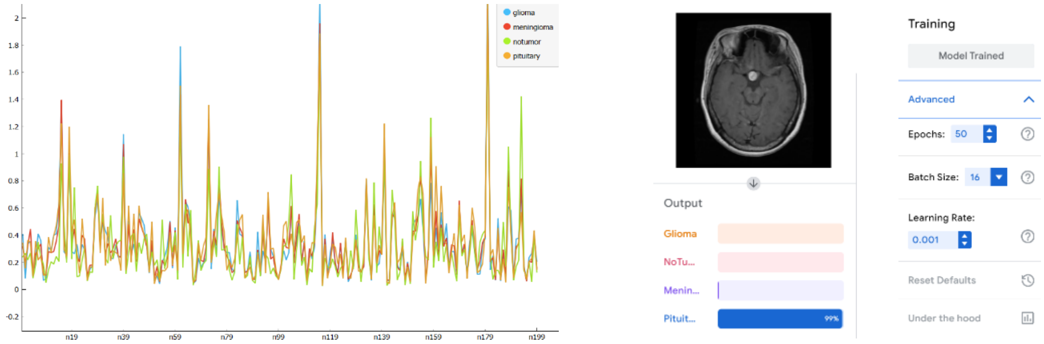


Fig. 13(a). Line plot of the mean calculated using hidden layers. (b)Model Training done on Google Teachable Machine.

5.2. Evaluation of the App

The user testing of the app was performed, the result of which is represented in the Table 4. Each row represents a patient with their unique Patient ID and corresponding MRI scan file. The “Actual Diagnosis” column contains the clinical diagnosis determined by medical professionals. The “AI Model Prediction” column reflects the output of the AI model when applied to the MRI scan, indicating whether a tumor or abnormalities were detected. The “Recommended Doctors” column suggests specialised doctors based on the AI model’s prediction.

Table 4. User Testing dataset collected from the App.

Patient ID	MRI Scan File	Actual Diagnosis	AI Model Prediction	Recommended Doctors	Personalised Sessions
001	patient001_mri_scan1.jpg	Glioblastoma	Tumour Detected	Dr. Smith (Neurologist)	Yes
002	patient002_mri_scan1.jpg	Meningioma	No Tumour Detected	Dr. Johnson (Radiologist)	No
003	patient003_mri_scan1.jpg	Pituitary	Tumour Detected	Dr. Anderson (Oncologist)	Yes
004	patient004_mri_scan1.jpg	Normal Brain	No Tumour Detected	N/A (No Abnormalities Detected)	No

5.3. Limitations and Future Growth

The current model’s performance is constrained by its reliance on the diversity and size of the available dataset, potentially limiting its robustness in capturing rare cases as shown in Table 5. Additionally, the model’s interpretability might be challenging due to the complexity of deep learning architectures, warranting further efforts in developing explainable AI techniques. The trajectory of this research holds promising avenues for future growth and expansion. Firstly, refining AI models with larger and more diverse datasets can enhance their accuracy and applicability across demographics. Collaboration with medical professionals and institutions for extensive clinical data can boost model reliability. Integration of advanced deep learning architectures like attention mechanisms and transformers could uncover deeper insights from MRI scans, increasing tumor detection accuracy. The integration of advanced deep learning architectures, such as attention mechanisms and transformers, holds the potential to extract deeper insights from MRI scans, further improving tumor detection accuracy. Expanding the scope to include CT scans or PET scans can create a comprehensive diagnostic platform for various brain anomalies. Incorporating explainable AI techniques enhances transparency. Collaborative efforts with regulators and ethical considerations ensure responsible AI deployment.

Table 5. Comparison of the developed model, MediScan, with existing models.

Technique	Methodology	"MediScan" Advantages
MediScan (Developed Model)	Neural network-based deep learning	- Specialised for brain tumour detection. Versatile, adapting to various tumour types. Higher accuracy rate in image classification. Ability to detect tumour at early stage.
Clustering-based Segmentation	Clustering algorithms, unsupervised	- Supervised learning for better accuracy.
Otsu's Segmentation	Thresholding technique, bi-level	- Handles nuanced tumour features better.
Multilevel Thresholding	Multilevel thresholding, optimization	- Eliminates manual threshold optimisation. Reduces expert parameter tuning.
Deep Learning-based Segmentation	Neural network-based deep learning	- Task-specific focus for optimised architecture. Improved accuracy for medical imaging.
DeepGlioma	Molecular subgroup identification, deep learning	- Broader applicability to different tumour types. Versatility for medical professionals.

6. Conclusion

In conclusion, the development of the AI-assisted brain tumor detection model using Orange and Google Teachable Machine has addressed the critical challenge of accurate brain tumor classification by integration of deep learning techniques and innovative algorithms. The multilevel threshold, neural network optimisation, and image preprocessing has yielded a robust AI model capable of distinguishing between various tumor types and normal cases with high accuracy rate. The translation of this advanced technology into a user-friendly smartphone application bridges the gap between cutting-edge research and practical healthcare applications. By including heatmap visualisation and diagnostic reports, the app empowers medical professionals to make informed decisions swiftly, thus shortening the diagnostic process. However, it is important to acknowledge that while the current model showcases promising results, certain limitations exist, such as the requirement for computational resources and the need for continual data refinement. Further research and improvisation could refine the model by feeding more diverse datasets to enhance generalisation, and fostering collaborations between medical experts and AI researchers.

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