Advancing Accuracy with Ai-Driven Approaches for Automated Detection and Segmentation of Brain Tumours

Dr. Sunil[1] Dr.Md. Masroof Ahmad[2] Hena Fatma[3]

[1] Associate Professor, Computer Engineering, Department of University Polytecnic, FoE&T Jamia Millia Islamia, New Delhi- 110025, India
Email Id: sunil@jmi.ac.in

[2] Associate Professor, Department of Physics & Computer Science, Magadh University, Bodhgaya, Bihar- 824234, India
Email Id: masroormachar@gmail.com

[3]Research Scholar, Department of Physics & Computer Science, Magadh University, Bodhgaya, Bihar- 824234, India
Email Id: henafatma555@gmail.com

ABSTRACT

The presence of brain tumours is a significant medical issue that calls for precise detection and diagnosis, particularly in the field of magnetic resonance imaging (MRI). The existing methods, which are relying on traditional image processing and conventional machine learning, face difficulties in accurately identifying the sites of tumours within complicated MRI scans. These images are frequently impacted by noise and have uneven picture quality. There have been several aspects of healthcare that have been revolutionized as a result of the introduction of artificial intelligence (AI), which has offered innovative opportunities for diagnostics and therapeutic approaches. The main aim of this study is to examine the improvement of accuracy via AI-based techniques for the automated identification and segmentation of brain tumours. This research is executed utilizing the Python programming environment. This research employed MRI datasets specifically for the detection of brain tumours. These datasets are accessible for utilization in accordance with the regulations established by the US Department of Health. The findings of this study indicated that the previous model achieves convergence at approximately 90% accuracy for both training and validation datasets. This indicates that the model identifies data patterns but lacks precision, potentially due to inadequate model complexity and inappropriate hyper parameters such as learning rate or batch size. This model demonstrates MobileNet's 95% accuracy in both training and validation, representing a significant enhancement over the prior model. MobileNet's depth and pre-trained features enable generalization, as seen by its ongoing accuracy improvement without overfitting. The previous model may be sufficient for basic jobs, whereas MobileNet is better for complex datasets needing greater precision. The proposed AI-based approach, which uses enhanced photo pre-processing, improves diagnostic precision and efficiency, helping healthcare workers improve patient outcomes.

Keywords: *Accuracy AI; Automated Detection; Segmentation; Brain Tumours; AI-driven Methodology.*

INTRODUCTION

The complex array of neoplasms known as brain tumours, which are caused by abnormal cellular proliferation within the delicate environment of the brain or the tissues that are next to it, present a great amount of difficulty for medical professionals [1]. It is important to note that this heterogeneity spans a wide range of tumour types, each of which exhibits distinct morphological, cellular, and physical properties. Astrocytomas, oligodendrogliomas, and glioblastomas are some of the subtypes that fall under the umbrella of gliomas, which are the most common primary brain tumours. An extra degree of intricacy is added by meningiomas, which are distinguished by their gradual growth from the meninges [1, 2, 3]. There are a variety of indications that can occur when malignancies that originated in other parts of the body spread to the brain and become metastatic. Because of the heterogeneity, there is an urgent requirement for accurate detection methods that are capable of addressing the intricacies involved in brain tumour classification. Because it is able to provide detailed images of soft tissues, MRI, which is well-known for its non-invasive technique, is an essential tool in neuroimaging. The capability of MRI to provide a full view of the brain is the primary reason for the significance of effective brain tumour detection using MRI. This view enables medical professionals to identify and differentiate anomalies with remarkable precision [1, 4]. In spite of the fact that MRI has many advantages, there are still difficulties in effectively distinguishing brain tumours from other complex scans. Traditional methods that rely on normal image processing and machine learning frequently fail to handle the numerous intricacies of MRI scans. This is because noise, artefacts, and fluctuations in image quality can mask important details [1, 5, 6].

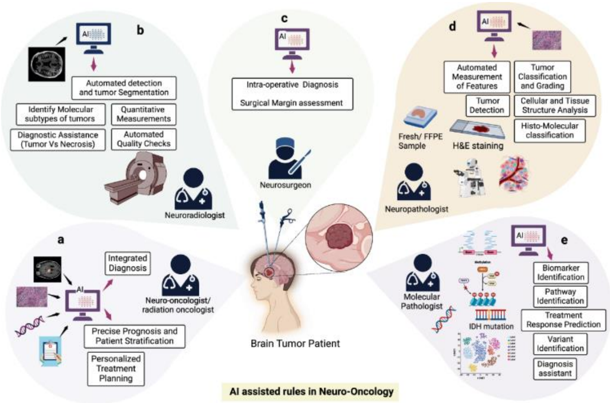

Figure 1: Multidisciplinary brain tumour management using AI [2]

The classification of brain cancer is increasingly acknowledged as a complex issue that machine learning can address. Algorithms capable of identifying patterns within extensive data sets might enhance the accuracy and efficiency of MRI tumour identification [1, 4]. This study examines an AI-based method that employs advanced image pre-processing to improve the detection of brain tumours using MRI data. It underscores the potential of AI to improve diagnostic precision and streamline clinical processes, thereby improving patient care, by demonstrating AI's efficacy. The subsequent section offers a thorough examination of the pertinent literature that pertains to this investigation.

LITERATURE REVIEW

The subsequent table elucidates the existing literature pertaining to enhancing accuracy through AI-driven methodologies for the automatic brain tumour detection and segmentation in brief.

Table 1: Related Works

AUTHORS AND YEAR	METHODOLOGY	FINDINGS
Addimulam et al., (2020) [7]	This study employed a secondary data review methodology to examine the status of deep learning-enhanced image segmentation for medical diagnostics.	This study showed that deep learning-enhanced image segmentation greatly improves medical diagnosis. CNN-based architectures' superior performance, attention mechanisms, generative models, transfer learning, and semi-supervised learning show deep learning's disruptive potential in this area.
Tripathi et al., (2021) [8]	The suggested method transfers feature maps directly to successive layers using encoder and decoder internal residual connections to avoid picture information loss. A more balanced network output is achieved.	External clinical validation was done by comparing algorithmic segmented images to those segmented manually by an experienced radiologist.
Krauze et al., (2022)	This study examined the imaging analysis workflow and how AI-driven imaging analysis in central nervous system	This study noted the growing technical complexities that may become increasingly separated from the clinic and the urgent need for clinician engagement to guide progress and

	cancers uses hand-crafted features, also known as traditional Machine Learning (ML), Deep Learning (DL), and hybrid analyses.	ensure that AI-driven imaging analysis conclusions are scrutinized like other clinical research.
Harishbhai et al., (2023)	This study developed a patch creation and selection approach for brain tumour segmentation using a modified U-Net deep learning architecture and appropriate normalization procedures.	Survival prediction relied on radiomic and clinical characteristics from segmentation outcomes. This study achieved a 0.69 accuracy in survival prediction during testing.
Wang et al., (2024)	Studies had to use MRI for brain tumour detection and segmentation, provide unambiguous performance indicators.	The best algorithms had 84% pooled lesion-wise Dice scores and 87% (patient-wise) and 86% (lesion-wise) sensitivity.
Onaizah et al., (2025)	This work proposes a Deep Learning-based approach to address outstanding concerns and improve cancer detection using AI. The study used a Siamese Convolutional Neural Network (SiCNN) to improve brain tumour diagnosis.	SiCNN successfully diagnosed brain tumours while safeguarding data during Deep Learning.

Research Gap

The technological gap between ML and AI brain tumour detection is due to limited access to large datasets for training resilient models, difficulties deciphering complex ML algorithms, and concerns about model generalizability across diverse populations and healthcare environments. [1, 4, 5]. Addressing this gap necessitates cooperative endeavours to compile extensive datasets, create interpretable AI methodologies, and implement stringent validation methods [7]. This research addresses the need to overcome these challenges to fully realize machine learning and artificial intelligence's potential to change brain tumour-based diagnostics and patient-based outcomes.

METHODOLOGY

The technique employed in this study can be delineated using the following sections:

Dataset details: This study employed MRI datasets collected for brain tumour identification, obtained from several worldwide regions to guarantee a comprehensive and inclusive analysis. These datasets are available for research in accordance with stringent regulatory compliance with the rules set forth by the US Department of Health, ensuring data protection and ethical utilization. A significant portion of the dataset originates from the United States, particularly New York City, and includes inputs from New Delhi, India, and many areas of Asia. Data from countries like India and China in Asia were crucial, providing a thorough demographic perspective. The data covers demographics for children under 15 who are especially susceptible to brain malignancies and people over 65, when incidence rates rise. Regional statistics on annual diagnoses and deaths in New York State and New Delhi enhance this rich information. Diversity, regulatory adherence, and demographic representation make the dataset ideal for developing and validating AI-driven brain tumour diagnostics algorithms, improving diagnostic accuracy and patient care. The architecture below shows the full AI-detected brain tumour detection procedure.

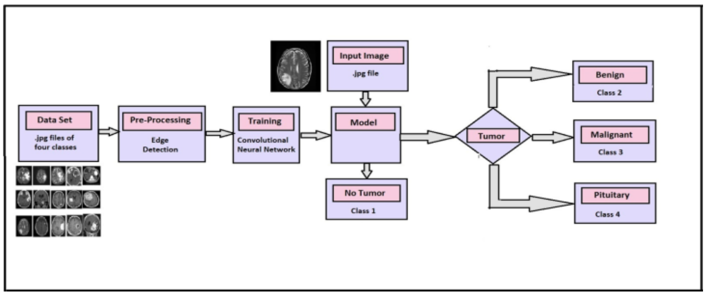

Figure 2: Proposed Architecture of this study

An explanation of each step is provided in the following paragraphs:

Dataset Collection

The collection includes brain MRI pictures classified as no tumour (Class 1), benign (Class 2), malignant (Class 3), and pituitary tumour (Class 4). The.jpg photos are from numerous public databases, ensuring strong training and testing representation.

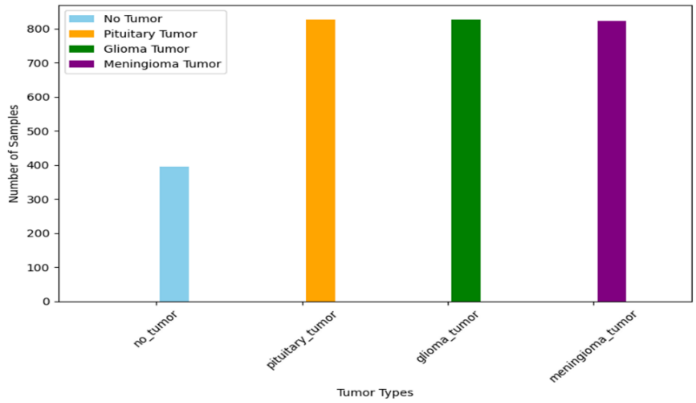

Figure 3: Distribution of Tumour Types in dataset used in this study

Pre-processing

Pre-processing improves image quality and gathers data for analysis. Edge detection highlights boundaries and important features in MRI images. This step removes noise and optimizes the dataset for processing.

Egmentation And Feature Extraction

Segmentation uses the threshold-based Otsu algorithm. This approach finds the best threshold value to distinguish cancer patches from the background, enabling accurate tumour spot isolation. This phase is critical for MRI malignancy detection. Feature extraction assesses tumour site form, texture, and intensity after segmentation. Accurate classification and analysis require these traits.

Training and Detection

The retrieved features are utilized to train machine learning models, chiefly ANNs and CNNs. CNNs are essential for analysing spatial hierarchies and patterns, facilitating the learning of intricate tumour characteristics and achieving great precision. The trained model categorizes incoming MRI pictures into one of four predetermined classifications. It initially determines the presence of a tumour. If identified, it subsequently categorizes the tumour as benign, malignant, or pituitary.

RESULTS AND DISCUSSIONS

In DenseNet Propagation, the training log reveals that the model has attained nearly perfect accuracy on the training dataset (approaching 100% accuracy from epoch 6), however the validation accuracy stabilizes, and the validation loss exhibits minimal reduction after several epochs. This is a quintessential indication of overfitting, as the model retains the training data rather than acquiring generic patterns that yield effective performance on novel data.

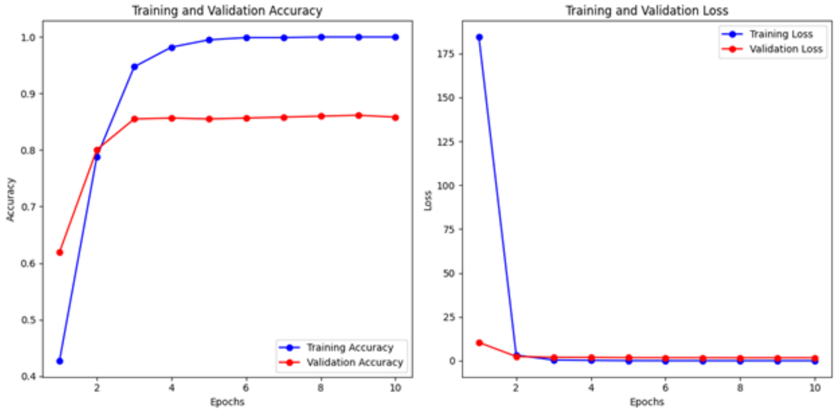

Figure 4: Training and Validation – Accuracy and Loss of DenseNet Model

ANN accuracy is 24% on training and validation datasets, indicating under fitting. Under fitting occurs when the model is very basic to identify data patterns, resulting in poor training and validation performance.

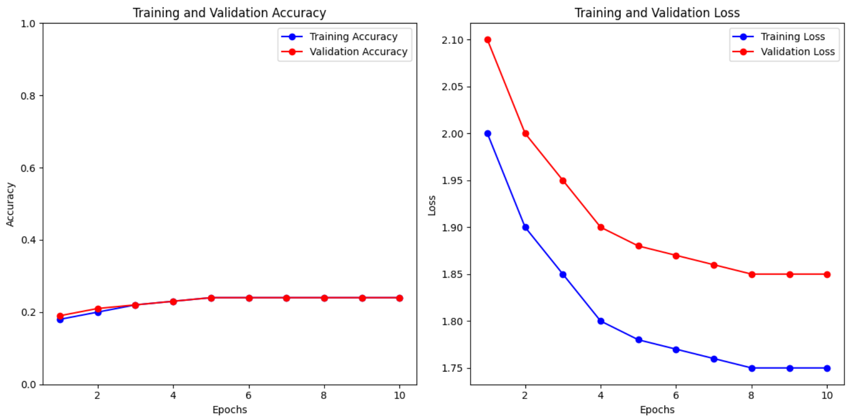

Figure 5: ANN Model – Training and the validation results

Loss measures how well the model's predictions match the labels, unlike accuracy, which measures sample classification accuracy. Model performance improves with lower values. Validation loss and accuracy evaluate the model's generalization on novel data, while approaches such as ReduceLROnPlateau modify the learning rate to optimize performance during periods of stagnation.

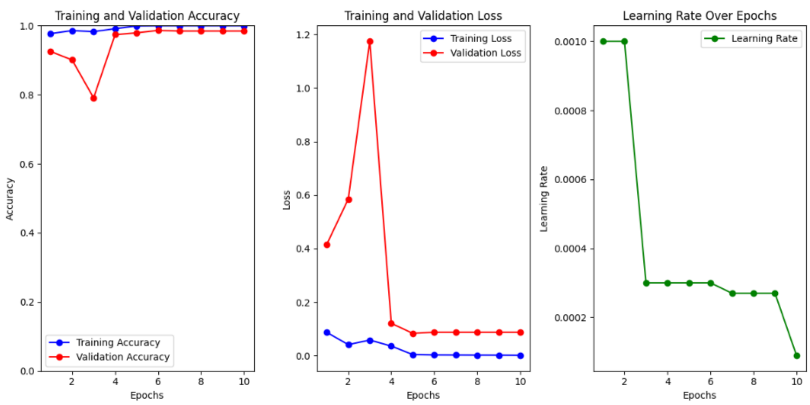

Figure 6: ResNet Propagation

During the initial epochs, the model attains a high training accuracy (~97.69%) and a satisfactory validation accuracy (~92.51%), although minor overfitting is observed as validation accuracy decreases while training accuracy remains

elevated. During succeeding epochs, validation accuracy markedly increases (~98.43%) when the learning rate is diminished, therefore stabilizing the training process and improving generalization.
The consistent reduction in training loss signifies good learning, whereas the variable validation loss implies possible overfitting or difficulties in generalization. Among the individual loss components, elevated rpn_bbox_loss and mrcnn_bbox_loss underscore the necessity for enhanced bounding box predictions, while reduced mrcnn_mask_loss and mrcnn_class_loss indicate the model's proficiency in learning masks and classifications.

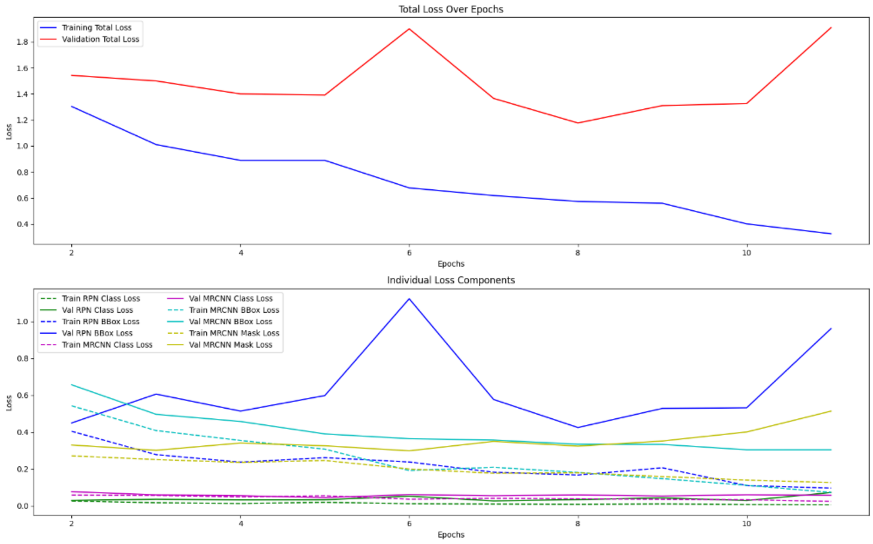

Figure 7: Illustration of Total Loss and Individual Loss

The convergence of training and validation accuracies at 95% in MobileNet signifies effective optimization and demonstrates the model's capability to generalize while accurately representing the dataset's patterns.

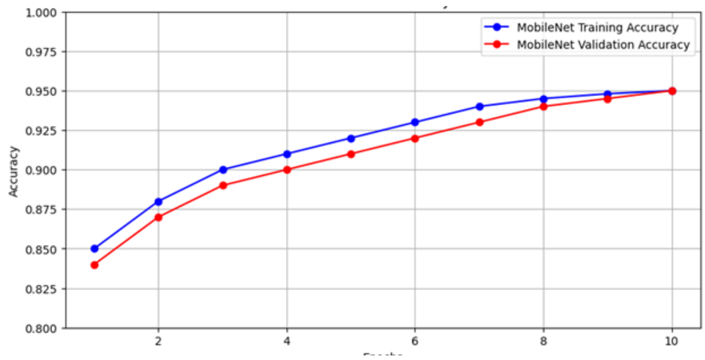

Figure 8: MobileNet Accuracy

The fact that the ANN model has a low accuracy that remains unchanged at 25% is indicative of under fitting. This could be the result of a too simplistic model design, an insufficient number of layers, or an insufficient number of neurons for the task at hand.

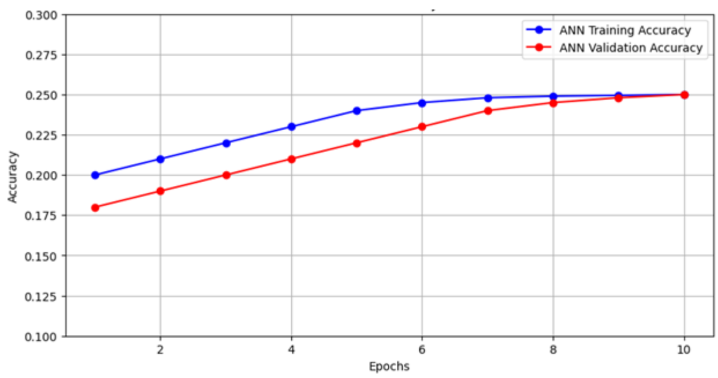

Figure 9: ANN model Accuracy

The performance comparison reveals that MobileNet outperforms ANN and is considered the best model because to its balanced effectiveness. On the other hand, DenseNet experiences overfitting, and ANN fails to perform well in the work, which highlights the importance of having intricate structures.

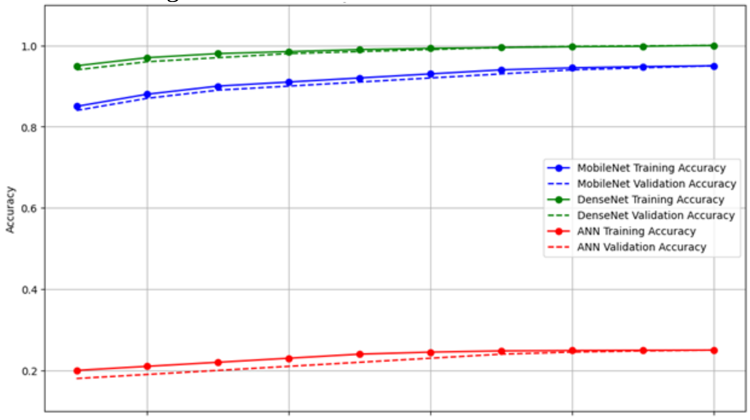

Figure 10: Accuracy of MobileNet; DenseNet and ANN

In the end, MobileNet outperforms the prior model by achieving an accuracy of 95% while also achieving increased generalization. This highlights the necessity of selecting an ideal architecture like as MobileNet for applications that require high precision and intricate datasets.

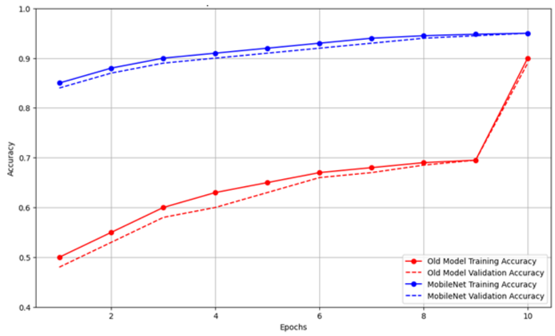

Figure 11: Comparison between Old Model and best proposed model.

Research and findings that indicated breakthroughs in artificial intelligence-based systems for medical image processing were carried out by Zubair Rahman et al. (2024) [1] and Wang et al. (2024) [11]. Both of these individuals conducted research and discoveries. More precisely, substantial gains were observed in the process of identifying brain cancers from the beginning. Zubair Rahman et al. (2024) [1] utilized EfficientNetB2 in conjunction with other approaches such as equalization and homomorphic filtering in order to enhance MRI image processing. This improved brain tumour identification accuracy. Their technique provides an emphasis on the enhancement of the feature extraction process, which is comparable to the emphasis placed on generalization and accuracy that is shown in MobileNet's performance in the results that have been presented. In other words, their strategy is similar to the method that has been proposed. Both of these studies illustrate the importance of using sophisticated designs such as EfficientNetB2 in order to obtain high accuracy while simultaneously reducing overfitting. MobileNet demonstrates a performance of 95%. Wang et al. (2024) [11] observed the increasing application of artificial intelligence systems for the detection and segmentation of brain tumours in their meta-analysis. The data indicate that MobileNet surpasses more basic structures such as artificial neural networks. The research findings and conclusions underscore the significance of model selection for optimal performance.

CONCLUSION

A comprehensive model comparison highlights the importance of architectural decisions for achieving optimal performance. Mobile Net routinely outperforms Dense Net and artificial neural networks, achieving 95% accuracy without overfitting. The lack of complexity and hyperparameters rendered the previous model, which attained 90% accuracy, ineffective. Mobile Net is appropriate for intricate datasets and realistic image classification problems because of its depth and pre-trained features, which enhance generalization. The proposed AI-driven approach demonstrates that artificial intelligence can enhance diagnostic accuracy and effectiveness. This approach employs comprehensive image pre-processing. Healthcare professionals seeking to improve patient outcomes may consider this strategy beneficial.

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