JETIR.ORG ISSN: 2349-5162 | ESTD Year : 2014 | Monthly Issue
JOURNAL OF EMERGING TECHNOLOGIES AND INNOVATIVE RESEARCH (JETIR)
An International Scholarly Open Access, Peer-reviewed, Refereed Journal

Enhancing Accuracy with AI-Powered Methods for Automated Detection and Segmentation of Brain Tumours

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

[1]Research Scholar, [2]Associate Professor, [3]Professor
[1]Computer Science, Department of Mathematics, Magadh University, Bodhgaya, Bihar, India
[2]Computer Engineering, Department of University Polytechnic, FoE&T, Jamia Millia Islamia, India
[3]Department of Physic & Computer Science, Mirza Ghalib College, Gaya, Bihar, India

Abstract : Brain tumours represent a critical medical challenge that requires precise detection and diagnosis, particularly in the context of magnetic resonance imaging (MRI). Traditional image processing methods and conventional machine learning techniques often struggle with accurately pinpointing tumour locations in complex MRI scans, which are often affected by noise and inconsistent image quality. The advent of artificial intelligence (AI) has revolutionised many areas of healthcare, offering new possibilities for diagnostic and therapeutic advancements. This study focuses on exploring how AI-based techniques can improve accuracy in the automated detection and segmentation of brain tumours. Conducted within the Python programming environment, the research utilises MRI datasets specifically designed for brain tumour detection. These datasets are available for use in compliance with regulations set forth by the US Department of Health.

The study's results show that the earlier model achieved a convergence rate of approximately 90% accuracy for both training and validation datasets. While this suggests the model could identify data patterns, it fell short of delivering precise results, likely due to issues such as insufficient model complexity and inappropriate hyperparameters, including learning rate or batch size. In contrast, the MobileNet model demonstrated a substantial improvement, reaching 95% accuracy in both training and validation, marking a clear advancement over the previous model. MobileNet's deeper architecture and use of pre-trained features allow for better generalization, evident in its consistent improvement in accuracy without overfitting. While the earlier model may suffice for simpler tasks, MobileNet proves more effective for complex datasets requiring higher precision. The proposed AI-based approach, which incorporates enhanced image pre-processing, boosts diagnostic accuracy and efficiency, ultimately aiding healthcare professionals in improving patient outcomes.

***IndexTerms* - Accuracy, AI, Automated Detection, Segmentation, Brain Tumours, AI-driven Methodology.**

I. INTRODUCTION

Brain tumours, a complex group of neoplasms caused by abnormal cell growth within the brain or surrounding tissues, present significant challenges for medical professionals [1]. These tumours are highly heterogeneous, encompassing a wide range of types, each with unique morphological, cellular, and physical characteristics. Among the most common primary brain tumours are gliomas, which include subtypes such as astrocytomas, oligodendrogliomas, and glioblastomas. Meningiomas, which arise from the meninges and grow gradually, add an additional layer of complexity to tumour classification [1, 2, 3]. Furthermore, metastatic brain tumours, which originate from cancers elsewhere in the body, present another set of challenges with varying symptoms. Due to this heterogeneity, there is a critical need for accurate detection methods that can address the complexities involved in brain tumour classification.

Magnetic resonance imaging (MRI), known for its non-invasive nature, is a crucial tool in neuroimaging because of its ability to provide detailed images of soft tissues. MRI's capacity to offer comprehensive views of the brain is essential for effective tumour detection, allowing healthcare professionals to identify and differentiate abnormalities with high precision [1, 4]. Despite its many advantages, MRI still faces challenges in distinguishing brain tumours from other complex conditions. Traditional image processing and machine learning techniques often struggle to handle the intricate details of MRI scans, as noise, artefacts, and fluctuations in image quality can obscure critical information [1, 5, 6].

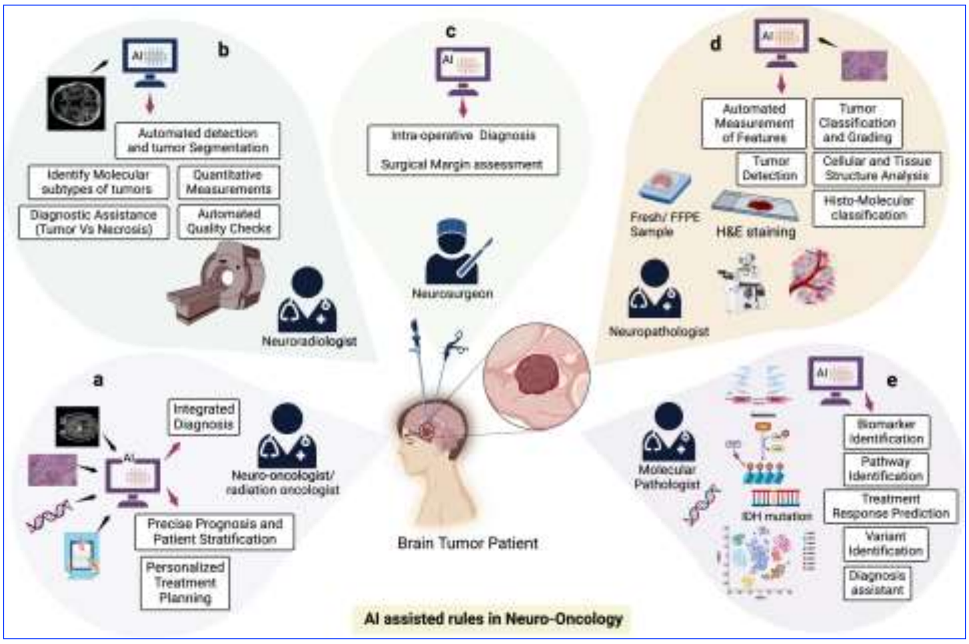

Fig.1: AI-empowered multidisciplinary brain tumour management [2].

Classifying brain cancer is increasingly recognised as a challenging task that machine learning can help solve. Algorithms that can detect patterns in large datasets have the potential to improve both the accuracy and efficiency of tumour identification in MRI scans [1, 4]. This study explores an AI-driven approach that utilises advanced image pre-processing techniques to enhance brain tumour detection from MRI data. It highlights AI's potential to boost diagnostic accuracy and streamline clinical workflows, ultimately leading to better patient care by demonstrating the effectiveness of AI. The following section provides a comprehensive review of the relevant literature related to this research.

II. Literature Review

The following table summarises the existing literature on improving accuracy through AI-based methods for the automated detection and segmentation of brain tumours.

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 cancers uses hand-crafted features, also known as traditional Machine Learning (ML), Deep Learning (DL), and hybrid analyses.	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 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.

Table 1: Existing Literature on Improving Accuracy Through AI-based Methods

III. 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 utilisation. 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.

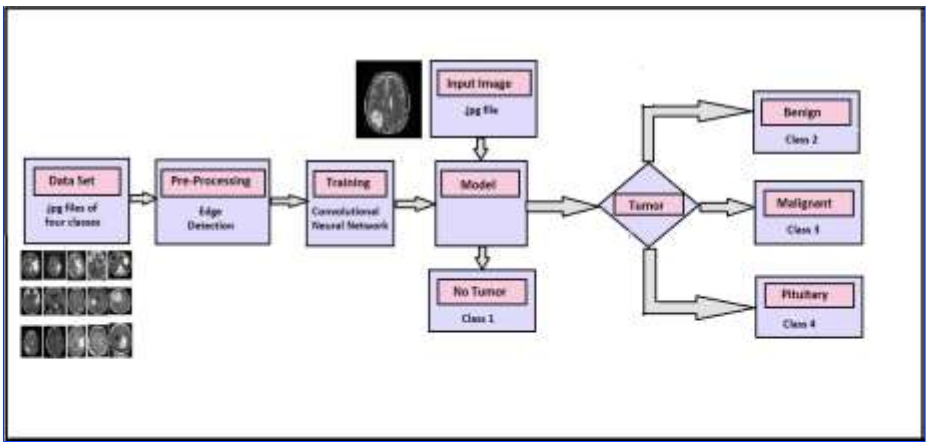

Fig. 2: Proposed Architecture of this study

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.

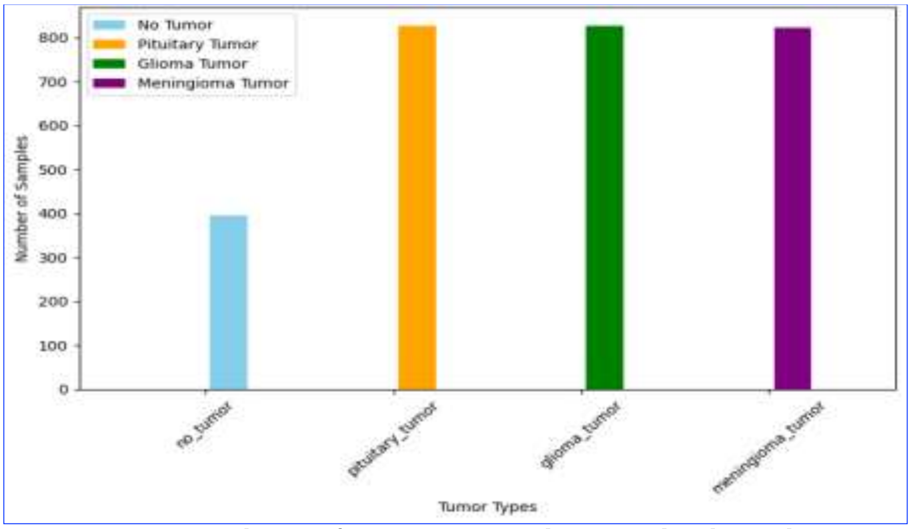

Fig. 3: Distribution of Tumour Types in dataset used in this study

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 optimises the dataset for processing.

Segmentation 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 utilised 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 categorises incoming MRI pictures into one of four predetermined classifications. It initially determines the presence of a tumour. If identified, it subsequently categorises the tumour as benign, malignant, or pituitary.

IV.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 stabilises, 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.

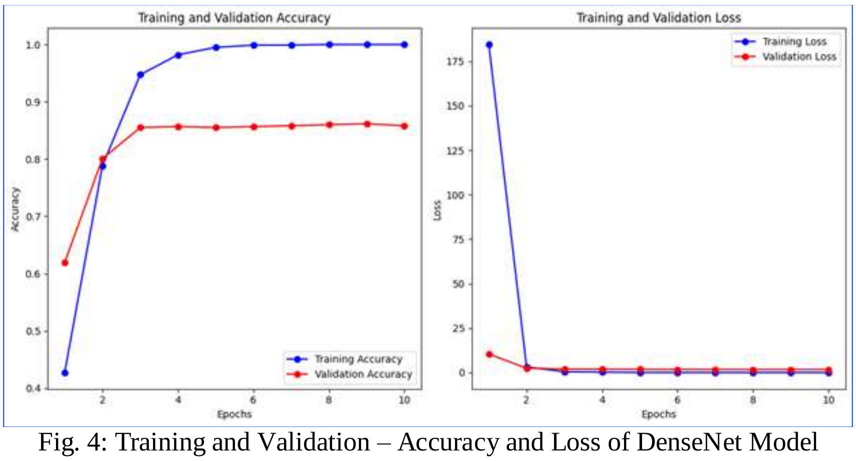

Fig. 4: Training and Validation – Accuracy and Loss of DenseNet Model

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.

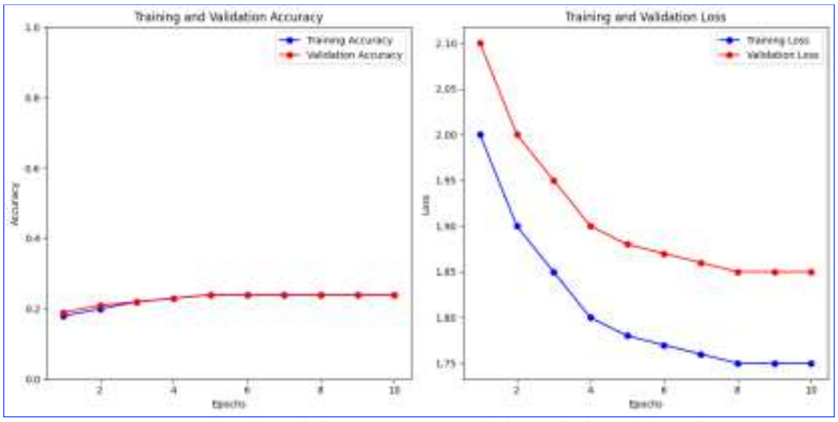

Fig. 5: ANN Model – Training and the validation results

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 optimise performance during periods of stagnation.

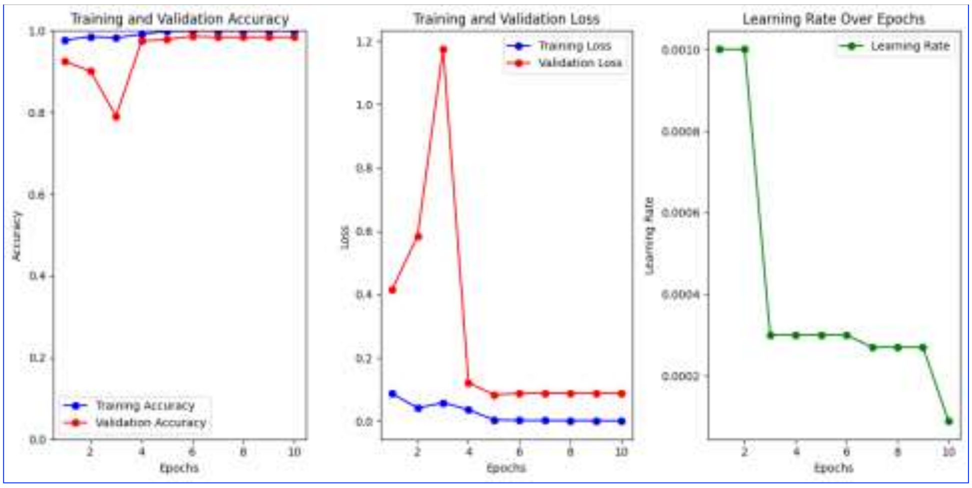

Fig. 6: ResNet Propagation

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 stabilising 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.

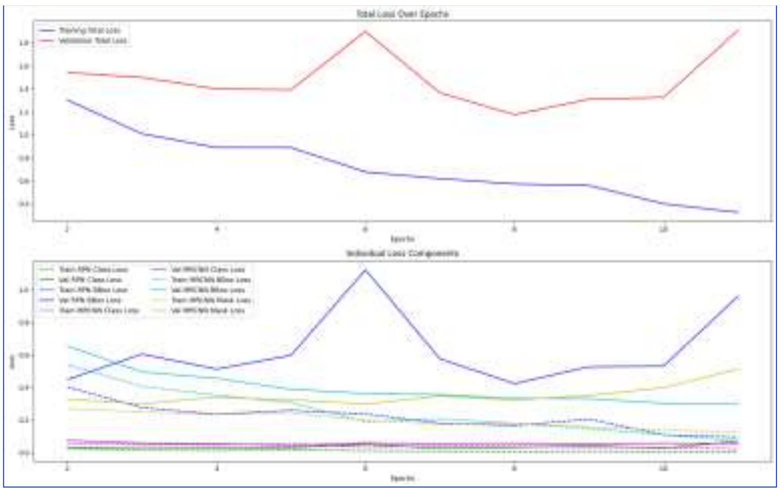

Fig. 7: Illustration of Total Loss and Individual Loss

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.

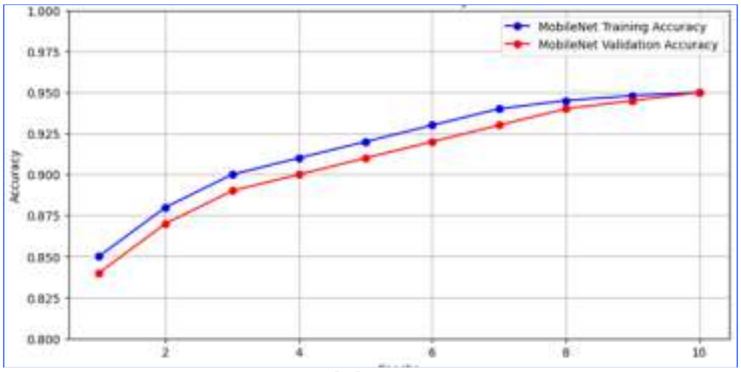

Fig. 8: MobileNet Accuracy

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.

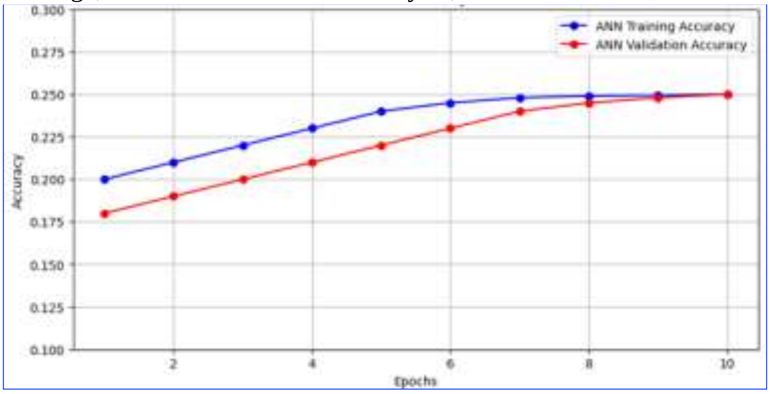

Fig. 9: ANN model Accuracy

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.

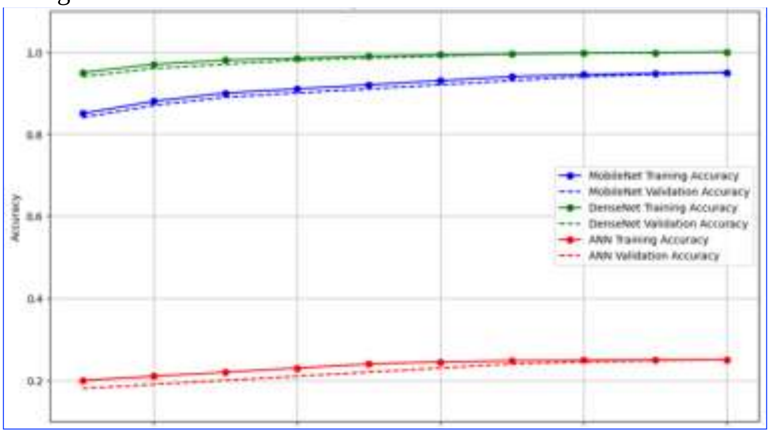

Fig.10: Accuracy of MobileNet; DenseNet and ANN

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.

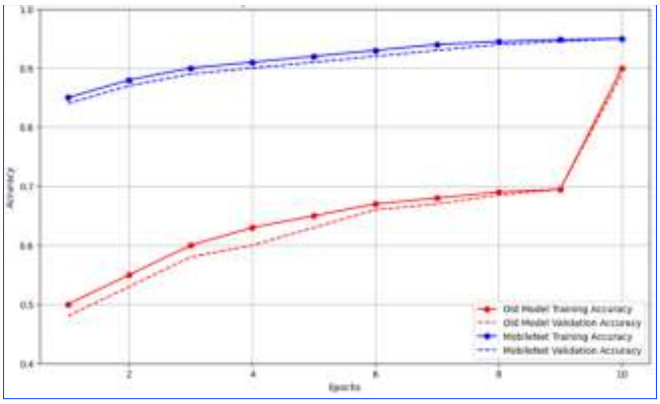

Fig. 11: Comparison between Old Model and best proposed model.

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] utilised EfficientNetB2 in conjunction with other approaches such as equalisation 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.

V. Conclusion

A thorough model comparison emphasises the significance of architectural choices in achieving optimal performance. MobileNet consistently outperforms DenseNet and artificial neural networks, reaching 95% accuracy without overfitting. In contrast, the previous model, which achieved 90% accuracy, was hindered by its lack of complexity and insufficient hyper-parameters. MobileNet’s deeper architecture and use of pre-trained features make it well-suited for complex datasets and real-world image classification tasks, improving generalization. The proposed AI-driven approach shows that artificial intelligence can significantly enhance diagnostic accuracy and efficiency through comprehensive image pre-processing. Healthcare professionals aiming to improve patient outcomes may find this approach highly beneficial.

REFERENCES

[1] Zubair Rahman, A. M. J., Gupta, M., Aarathi, S., Mahesh, T. R., Vinoth Kumar, V., Yogesh Kumaran, S., & Guluwadi, S. (2024). Advanced AI-driven approach for enhanced brain tumour detection from MRI images utilizing EfficientNetB2 with equalization and homomorphic filtering. *BMC Medical Informatics and Decision Making*, *24*(1), 113.

[2] Khalighi, S., Reddy, K., Midya, A., Pandav, K. B., Madabhushi, A., & Abedalthagafi, M. (2024). Artificial intelligence in neuro-oncology: advances and challenges in brain tumour diagnosis, prognosis, and precision treatment. *NPJ Precision Oncology*, *8*(1), 80.

[3] Sinha, A., & Kumar, T. (2024). Enhancing Medical Diagnostics: Integrating AI for precise Brain Tumour Detection. *Procedia Computer Science*, *235*, 456-467.

[4] Krauze, A. V., Zhuge, Y., Zhao, R., Tasci, E., & Camphausen, K. (2022). AI-Driven image analysis in central nervous system tumours-traditional machine learning, deep learning and hybrid models. *Journal of biotechnology and biomedicine*, *5*(1), 1.

[5] Cè, M., Irmici, G., Foschini, C., Danesini, G. M., Falsitta, L. V., Serio, M. L., ... & Cellina, M. (2023). Artificial intelligence in brain tumour imaging: a step toward personalized medicine. *Current Oncology*, *30*(3), 2673-2701.

[6] Kaboudan, A., & Salah Eldin, W. (2023). AI-Driven Medical Imaging Platform: Advancements in Image Analysis and Healthcare Diagnosis. *Journal of the ACS Advances in Computer Science*, *14*(1).

[7] Addimulam, S., Mohammed, M. A., Karanam, R. K., Ying, D., Pydipalli, R., Patel, B., ... & Natakam, V. M. (2020). Deep Learning-Enhanced Image Segmentation for Medical Diagnostics. *Malaysian Journal of Medical and Biological Research*, *7*(2), 145-152.

[8] Tripathi, S., Verma, A., & Sharma, N. (2021). Automatic segmentation of brain tumour in MR images using an enhanced deep learning approach. *Computer Methods in Biomechanics and Biomedical Engineering: Imaging & Visualization*, *9*(2), 121-130.

[9] Krauze, A. V., Zhuge, Y., Zhao, R., Tasci, E., & Camphausen, K. (2022). AI-Driven image analysis in central nervous system tumours-traditional machine learning, deep learning and hybrid models. *Journal of biotechnology and biomedicine*, *5*(1), 1.

[10] Harishbhai, P. B. (2023). *Automated Brain Tumor Segmentation and Survival Prediction using Multimodal MRI* (Doctoral dissertation, Gujarat Technological University Ahmedabad).

[11] Wang, T. W., Shiao, Y. C., Hong, J. S., Lee, W. K., Hsu, M. S., Cheng, H. M., ... & Wu, Y. T. (2024). Artificial intelligence detection and segmentation models: a systematic review and meta-analysis of brain tumours in magnetic resonance imaging. *Mayo Clinic Proceedings: Digital Health*, *2*(1), 75-91.

[12] Onaizah, A. N., Xia, Y., & Hussain, K. (2025). FL-SiCNN: An improved brain tumour diagnosis using siamese convolutional neural network in a peer-to-peer federated learning approach. *Alexandria Engineering Journal*, *114*, 1-11.