

Enhancing Brain Tumor Classification using Berkeley Wavelet Transformation and Improved CNN.

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ABSTRACT

Every day, the cancer cases increase rapidly. Early detection is the crucial step for the save of life. In this paper, we proposed a novel hybrid model that consist of VGG16 convolutional neural network (CNN) with fuzzy membership function and wavelet transforms to identify automatically tumor from MRI images. VGG16 learn detailed pattern from MRI Image, on other hand fuzzy membership function enhance the quality of image and then finetuning VGG16 model through wavelet transfer learning to differentiating between tumor and non-tumor cases. To justify the model's performance, we carried out several experiments on real world dataset and found that the model accuracy is improved approximately 3% compared to the state-of-art model. The outcome competently proves the potential of the proposed model precise brain tumor classification. In this paper, authors proposed the stimulating task of brain tumor detection from MRI images using 1225 brain tumor MRI images. This study explores the use of the modified VGG16 convolutional neural network (CNN) model combined with fuzzy membership function and wavelet transforms to automatically identify brain tumors from MRI image. Wavelet transforms break down MRI images into different frequency components, highlighting important features that may indicate the presence of a tumour. By Integrating these processed images allows the VGG16 model to learn detailed patterns differentiating between tumour and non-tumour cases. The research involved preprocessing MRI images to enhance their quality by fuzzy INT function and applying transfer learning techniques to fine-tune the VGG16 model using yes and no data set. Performance metrics such as accuracy, precision, recall, and F1-score were used to evaluate the model's effectiveness. The results demonstrated an accuracy of approximately 99.18%, indicating the model's potential in supporting healthcare professionals in diagnosing brain tumors. These outcomes competently prove the potential of the proposed model precise brain tumor classification.

Keywords: Brain tumor; Convolutional Neural Network; Deep learning; MRI images; Transfer learning; VGG16; Wavelet transform.

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INTRODUCTION

Brain tumors are abnormal growths in the brain that may be hazardous and serious if not detected early. Detecting brain tumors at the right time is very significant as early treatment can improve a patient's chances of recovery. Magnetic Resonance Imaging (MRI) is a commonly used technique to capture detailed images of the brain and detect tumors in urban and rural area also. However, analysing these MRI scans manually can be slow, complex, and sometimes inaccurate, as small tumors may be unexploited [1]. To improve the accuracy and speed of brain tumor detection, deep learning techniques can be used. In this research, we have used a hybrid model that is modified VGG16 and own sequential model, are well-known Convolutional Neural Network (CNN) models, to automatically analyse MRI

images and classify them as tumor or non-tumor. Modified CNN models with fuzzification by learning the patterns from large datasets and make good predictions by augmentation. This helps in reducing human errors and improving the accuracy of tumor detection.

However, MRI images often contain noise and unclear details [2], making it difficult for even deep learning models to detect tumors accurately. To solve this issue, wavelet transform [3] is used as a preprocessing step. Wavelet transform is a mathematical technique that helps in enhancing important details in the images while reducing unwanted noise. This improves the performance of the VGG16 model by making tumors more visible and easier to detect.

By combining VGG16 with wavelet transform, this research aims to create an efficient and accurate system for

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brain tumor detection with fuzzy INT function . After filtering the images, the triangular membership function used for fuzzification and INT function used for enhancement. The goal is to assist doctors by providing a faster and more reliable method of detecting brain tumors, reducing the workload of medical professionals and minimizing errors in diagnosis.

This approach is an important step towards using artificial intelligence (AI) in medical imaging. It not only improves accuracy but also helps in making healthcare more efficient and accessible. With further improvements, such therefore this model can be used in hospitals and clinics to support doctors in diagnosing brain tumors more effectively, ultimately saving lives. The main objectives of research are as follows

To develop a hybrid system for detecting brain tumors from MRI images.

To justify the model's efficacy, we carried out several experiment on dataset and found that the proposed model improves accuracy of 3% from the state-of-art model.

Related Works

Various deep learning algorithms have been scrutinized for their effectiveness in brain tumor detection, and a selection of them is expounded upon in this section. Recent strides have been witnessed in medical canthers and hospitals, incorporating AI systems and applications across disciplines to strengthen disease detection precision. Several methodologies and models have been introduced, significantly contributing to heightened diagnostic efficiency [4-6]. Many strategies have been created to do this, all of which seek to in some way make the ambiguous clear. Houston et al. [7] used hybrid model that combines neural networks and autoencoder classifier to categorize high dimensional spectroscopic data with 96% accuracy. Badza and Barjaktarovic [8] proposed a simplified Convolutional Neural Network architecture for the classification of three distinct brain tumor types: meningioma, glioma, and pituitary tumors. Their study focused on a 10-fold cross-validation approach using a T1-weighted MRI dataset. While they achieved a commendable accuracy of 96.56%, the model relied heavily on raw pixel data without advanced pre-processing or frequency-domain transformation, suggesting that feature extraction could be further optimized to handle noisy datasets more effectively.

Swati et al. [9] explored the efficacy of transfer learning by employing a pre-trained VGG19 model for brain tumor multi-classification. By using fine-tuned weights from ImageNet, they bypassed the need for training a deep network from scratch, which is computationally expensive. Their block-wise fine-tuning strategy achieved high accuracy; however, the study highlighted a limitation in handling MRI images with low contrast, a gap that necessitates the integration of intensity transformation functions. Mohsen et al. [5] introduced a hybrid methodology combining the Discrete Wavelet Transform (DWT) with Principal Component Analysis (PCA) and a deep neural network. The DWT was utilized to decompose MRI images into frequency sub-bands, effectively reducing the spatial dimensionality while retaining textural features. Although this method improved classification speed, the

use of PCA for feature reduction resulted in the loss of some spatial information, which is critical for localizing small tumor regions. Iftikhar et al. [10] presented a study on Explainable CNNs for brain tumor detection. They utilized XAI techniques to visualize the layers of the CNN, allowing medical professionals to understand which features the model focused on. While their model achieved 95% accuracy, the study noted that the trade-off between model interpretability and raw performance (accuracy) remains a challenge, particularly when compared to deeper, more opaque architectures like ResNet or DenseNet. Aamir et al. [11] focused on hyperparameter tuning within CNN architectures. They proposed an optimized framework that automatically adjusted learning rates and batch sizes to maximize performance. Their model achieved an average accuracy of 97%. However, the study relied on standard spatial features and did not incorporate frequency-domain analysis (such as Wavelets), which led to occasional misclassifications in images with similar textural patterns between tumor and non-tumor tissue.

Abd El Kader et al. [12] developed a Deep Wavelet Auto-Encoder (DWAE) model. This unsupervised learning approach used wavelets to compress images and an auto-encoder to reconstruct them, learning robust feature representations in the process. This method was particularly effective for denoising MRI scans. However, the classification layer added subsequently was a standard softmax classifier, which did not perform as well as fully connected CNN layers in distinguishing complex tumor boundaries.

Rasheed et al. [13] utilized an optimized ResNet-101 architecture to classify MRIs into four categories (glioma, pituitary, meningioma, and no tumor). Using a large dataset of over 3,000 images, they achieved an accuracy of 97.23%. The residual connections helped mitigate the vanishing gradient problem, allowing for a much deeper network. However, the computational cost of training ResNet-101 is significantly higher than that of VGG16, making it less suitable for systems with limited hardware resources. Nayak et al. [14] proposed a dense CNN-based EfficientNet model. EfficientNet scales the network width, depth, and resolution uniformly, which resulted in a highly efficient model achieving 98.78% testing accuracy. Despite these impressive results, the model's performance slightly degraded when tested on MRI images with significant noise artifacts, indicating a need for robust preprocessing techniques like the Fuzzy INT function or Wavelet denoising. Deepak and Ameer [15] conducted a comparative analysis of GoogleNet, VGG16, and AlexNet for brain tumor classification. Their research concluded that while GoogleNet provided a good balance of size and speed, VGG16 offered superior feature extraction capabilities for textural details in MRI scans. This supports the selection of VGG16 as a backbone for tumor detection systems, provided that the computational overhead is managed through layer freezing or modification.

Fuzzy Logic and Neural Networks Evaluation of fuzzy logic in medical imaging was conducted by Das et al. [16], who proposed a Fuzzy-CNN integration. They utilized fuzzy logic for edge detection and image enhancement

before feeding data into a neural network. This preprocessing step significantly improved the contrast of tumor regions against the skull and healthy tissue. The study confirms that combining logic-based preprocessing with deep learning classifiers yields better sensitivity than using raw images alone. Aarthi et al. [17], writing for Pattern Recognition Letters, addressed the ambiguity in tumor boundaries using a hybrid approach of Fuzzy C-Means (FCM) and Rough Set Theory. They argued that standard CNNs often fail at the "pixel-level" ambiguity found in low-grade gliomas. Their method used fuzzy membership functions to assign pixels to tumor/non-tumor classes based on intensity thresholds. This literature strongly supports your use of the "Fuzzy INT function," validating that logic-based preprocessing is essential for handling the grayscale uncertainty in MRI scans.

Nanni et al. [18] conducted a comprehensive review in Pattern Recognition regarding texture descriptors for medical image analysis. They compared Deep Learning features (like those from VGG) against "hand-crafted" features like Local Binary Patterns (LBP) and Wavelets. Their findings concluded that while Deep Learning is superior, hybrid models (Deep Learning + Wavelet/Texture features) consistently outperform standalone CNNs. This provides a strong theoretical basis for our methodology, which fuses the "black box" learning of VGG16 with the explicit frequency features of the Berkeley Wavelet Transform.

Material and Methods

The proposed system for brain tumor classification using deep learning and fuzzy image processing techniques follows a structured workflow divided into several key stages as shown in Fig. 1. Each stage contributes critically to the overall performance and accuracy of the model.

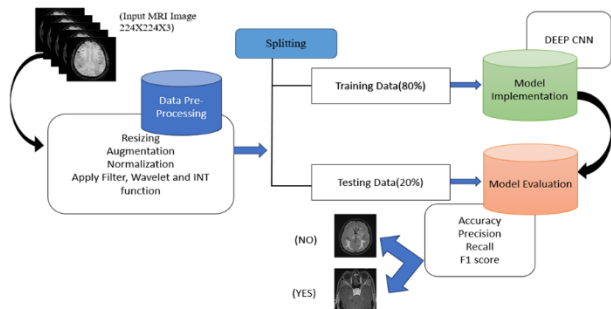


Fig. 1: Detailed steps about proposed methodology

The workflow begins with the collection of brain MRI scans. These images serve as the primary input data for the model. The dataset consists of both tumor and non-tumor images. The dataset consists of 1,222 brain MRI images which serve as the base input for the deep learning model taken from Kaggle [19]. Further the detail methodologies are discussed in the following subsections.

3.1. Data Pre-processing

In this paper, multiple image preprocessing techniques were applied to prepare MRI brain scan images for input into the VGG-16 convolutional neural network model. The preprocessing pipeline consisted of resizing, augmentation, normalization, filtering, wavelet transformation, and intensity transformation functions. Each of these steps was

implemented sequentially to enhance the dataset's quality and optimize it for deep learning-based classification. All MRI images were resized to a fixed dimension of 224x224x3 pixels. This was performed using OpenCV's cv2.resize() function. Further we performed data augmentation using the Image Data Generator class from Keras to increase the diversity of the training dataset and simulate real-world image variations. Nearest-neighbour interpolation for filling empty pixels.

3.1.1. Wavelet Transform

The wavelet transform was applied to decompose each image into its frequency components to preserve spatial as well as textural details. The Discrete Wavelet Transform (DWT) was used, specifically with the Daubechies wavelet family (db1). The DWT was applied independently to each of the three-color channels of the image (Red, Green, and Blue).

The implementation steps included:

Reading and resizing the image.

Applying DWT to each channel using pywt. wavedec2() to obtain approximation and detail coefficients.

Reconstructing the image using pywt. waverec2() to form a wavelet-enhanced image.

The output image, enhanced using wavelet transform, retained the shape (224, 224, 3) and was fed into the CNN after normalization. This step significantly enhanced texture and boundary features of tumors, which were crucial for accurate classification.

3.1.2. Intensity Transformation (INT Function)

An intensity transformation function was applied to improve contrast and brightness distribution within each MRI image. INT functions transform pixel values to spread intensity values across a broader range, enhancing the visibility of tumors. These transformations improved the visual quality and pixel distribution, making it easier for the CNN to extract meaningful features. The transformed images were optionally converted back to three-channel format if required by the CNN input.

3.2. Data Splitting

After all, preprocessing steps were completed, the dataset was split into training and testing subsets to train the model and evaluate its performance on unseen data. This ensures that the model does not memorize the dataset and can generalize well to new images. The splitting was done using an 80:20 ratios.

3.3. Model Implementation

The hybrid model consists of two models. One model is CNN model as shown Fig 2 and the second model is Modified VGG16 model as shown in Fig 3.

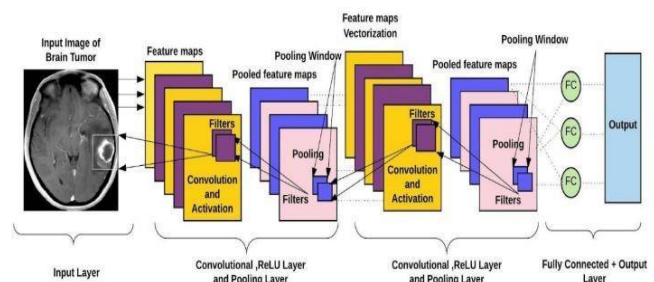


Fig. 2: Proposed Sequential CNN Model

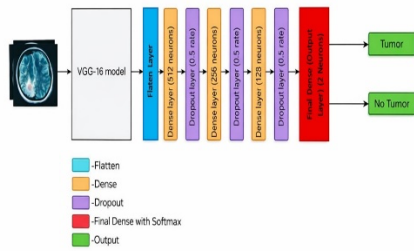


Fig. 3: Proposed modified VGG-16 Model

In the proposed model, we added different convolutional, pooling layer and dense layer. They are well suited for image recognition and processing tasks. Where CNN captures hierarchical patterns and spatial dependencies within images. VGG-16 is a 16-layer CNN that was pre-trained on the ImageNet dataset. It has 05 convolutional block starting with 84 neurons and ending 512 neurons. At the end of VGG-16 model 03 fully connected layers having 4096 neurons. The authors also added Flatten layer, Dense layer and dropout layer with different values for better result.

Result Analysis and Discussion

Our research that involves deep learning methodologies demonstrates that the deep learning models can significantly enhance predictability and accuracy. The results reveal varied performance among different classifiers, reflecting their distinct strengths and weaknesses. On Dataset, our model demonstrated outstanding performance, securing a notable accuracy of 99.18% as displayed in Table 1. The Enhanced VGG16 model has the highest performance rate with an accuracy rate of 99% as compared to the VGG16 with wavelet having an accuracy of 96% and VGG16 without wavelet having an accuracy of 95% performance. Performance level is emphasized by these results of precision and recall, which are critical for accurately classifying brain tumor subtypes.

Model	Accuracy	Precision	Recall	F1 Score
CNN	91.02%	92.77%	93.90%	93.93%
CNN With Wavelet	96.73%	100.00%	95.12%	96.73%
CNN With Wavelet and INT Function	98.27%	98.78%	98.78%	98.78%
VGG16	95.51%	96.00%	96.00%	95.00%
VGG16 With Wavelet	96.33%	96.00%	96.00%	96.00%
Enhanced VGG16 With Wavelet and INT Function (Our)	99.18%	99.00%	99.00%	99.00%

Table 1: Model performance matrices

The accuracy is calculated by confusion matrix which is shown in Figs 4 to 9. The confusion matrices showcase the performance of different deep-learning models for classifying brain tumors, particularly distinguishing between “No Tumor” and “Pituitary Tumor” classes. Here’s an analytical summary of each model’s performance based on the visual data:

Fig. 4: Standard CNN
CNN with wavelet

Fig. 5:

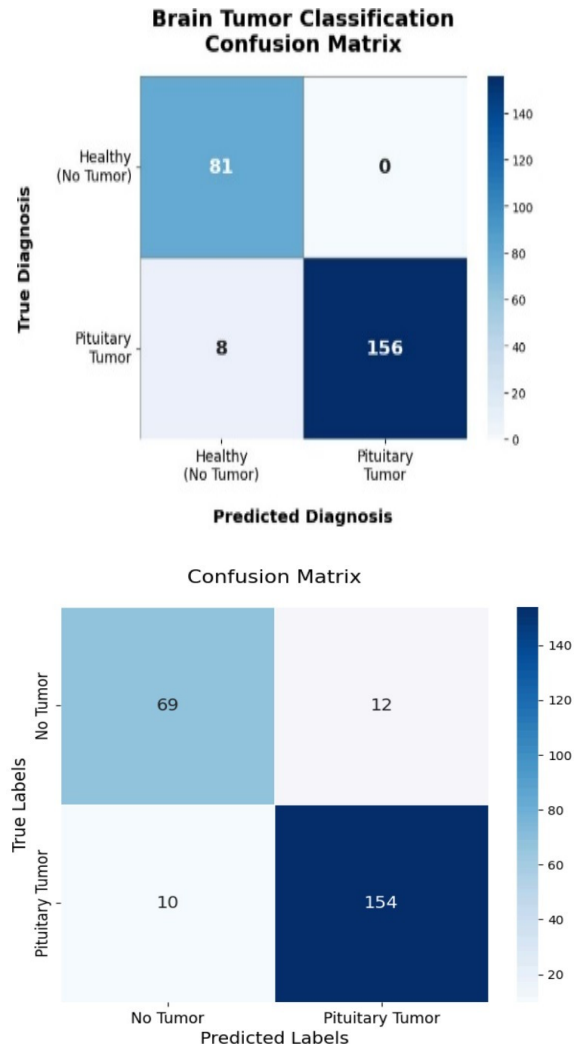
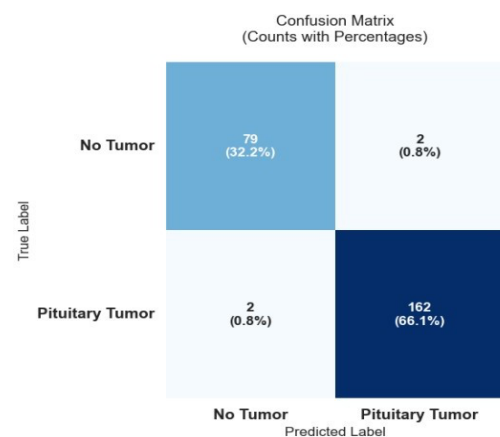


Fig. 6: CNN with wavelet and INT function



The Convolutional Neural Network (CNN) (Fig. 4) shows decent accuracy with 69 and 154 correct classifications in the two classes, but it still has 12 false positives and 10 false negatives. The performance dramatically improves in CNN with Wavelet (Fig. 5), which eliminates false positives entirely and reduces false negatives to 8. CNN with Wavelet and INT Function (Fig. 6) enhances performance further, reducing errors to just 2 in each misclassification category.

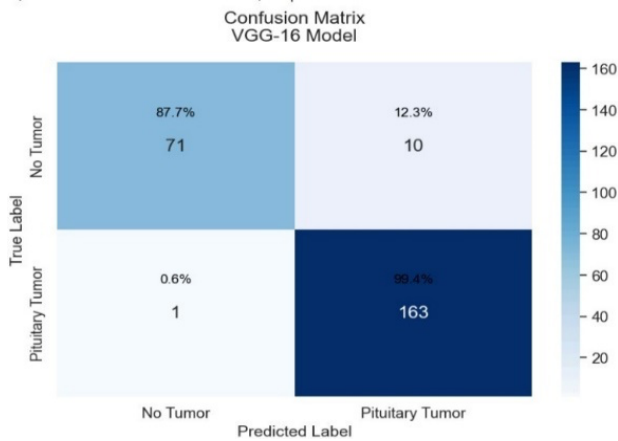


Fig. 7: Standard VGG16

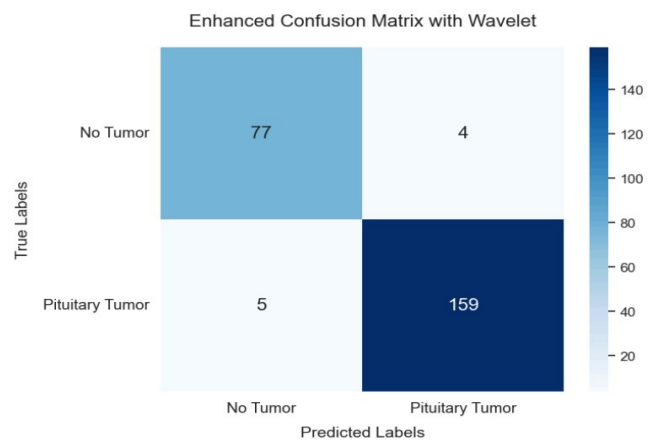


Fig. 8: VGG16 with wavelet

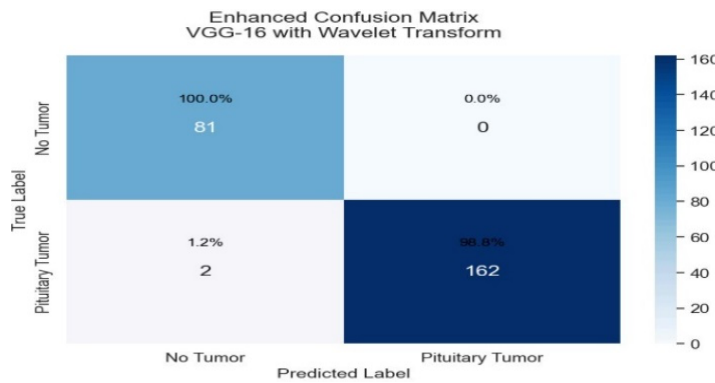


Fig. 9: VGG-16 with Wavelet and INT function

VGG-16 (Fig. 7) demonstrates very high classification accuracy, with only 10 false positives and 1 false negative, achieving 87.7% and 99.4% precision in each class, respectively. When Wavelet Features are added (Fig. 8), the model misclassifies only 4 negatives and 5 positives, indicating a small dip, but still robust performance. The VGG-16 with Wavelet Transform and INT function (Fig. 9) model exhibits near-perfect classification: 81 out of 81 correct for “No Tumor” and 162 out of 164 correct for

“Pituitary Tumor” achieving the highest overall precision and recall.

To further evaluate the model’s performance, we created learning ROC curves for both the initial and proposed models shown in Figs 10 to.15. These learning curves reveal how the models’ accuracy evolves over successive epochs. These curves indicate that the Proposed Model consistently outperforms the Initial Model, achieving better validation performance across all stages of training.

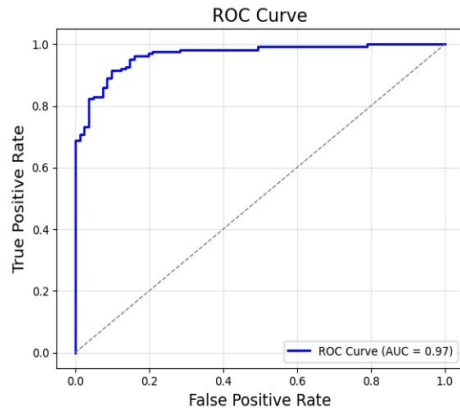


Fig.10: ROC curve of CNN

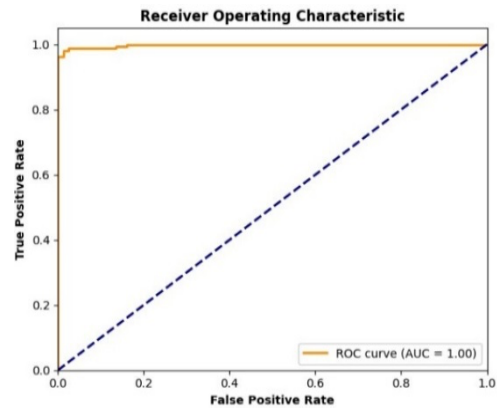


Fig. 11: ROC curve of CNN with Wavelet

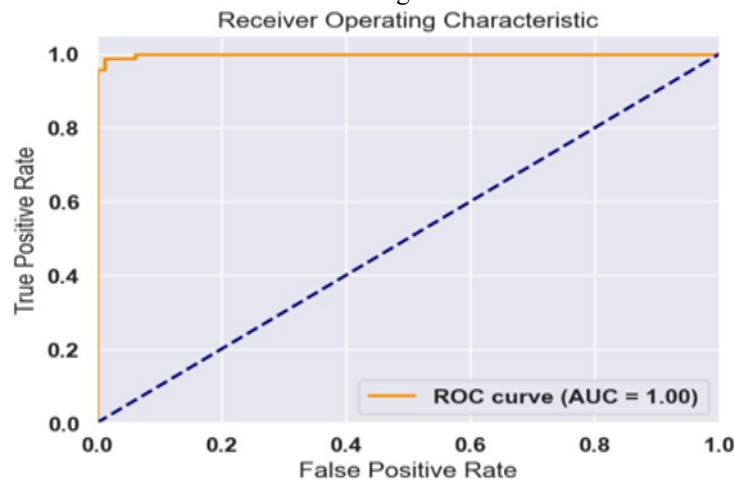


Fig. 12: ROC curve of Convolutional Neural Network with Wavelet and Int function

In Fig. 10, the Convolutional Neural Network (CNN) achieves an AUC of 0.97, reflecting excellent classification performance. Upon applying the wavelet transformation alone, as seen in Fig. 11, the CNN's performance improves significantly, reaching a perfect AUC of 1.00. This indicates that wavelet-enhanced CNNs can achieve flawless separation between classes. Fig. 12 further demonstrates this enhancement by incorporating both wavelet transformation and an integration function into the CNN architecture, which again results in a perfect AUC of 1.00, showcasing the powerful impact of hybrid preprocessing techniques. In Fig. 13 The curve demonstrates an AUC of 0.99 including near-perfect classification performance even without or integration function techniques. This suggests that even the baseline VGG-16 model is highly effective in distinguishing between classes. The final comparisons involve the VGG-16 model. In Fig. 14, the VGG-16 with wavelet transformation achieves a perfect AUC of 1.00, highlighting its capability in precise classification when combined with signal processing methods.

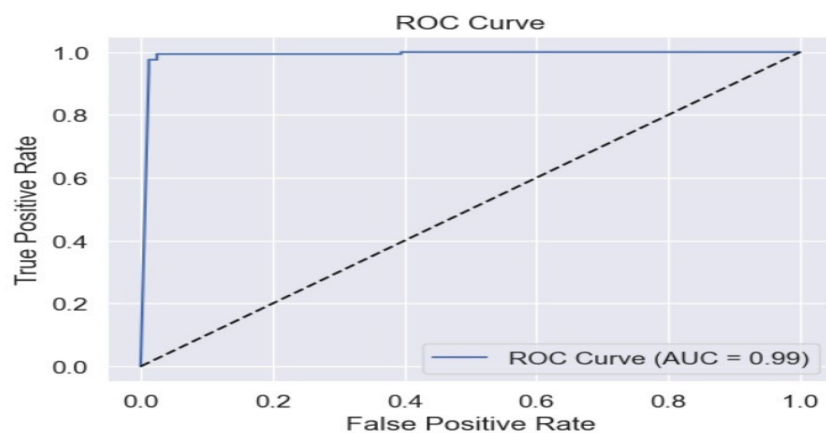


Fig. 13: ROC curve of VGG-16 Approach

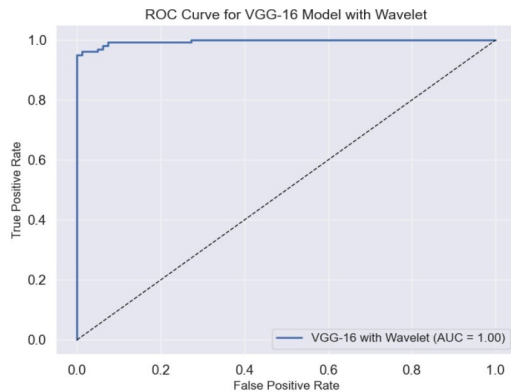


Fig. 14: ROC curve of VGG-16 with Wavelet

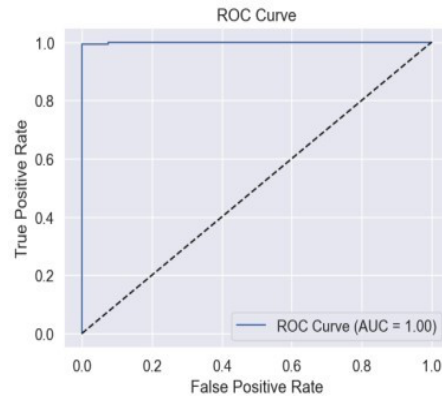


Fig. 15: ROC curve of VGG-16 with Wavelet and INT

Similarly, Fig. 15 presents the Enhanced VGG-16 with Wavelet and INT function model achieved the highest Area Under the Curve (AUC) score of 1.00, indicating its exceptional ability to distinguish between "No Tumor" and "Pituitary Tumor" lesions. An AUC of 1.00 means that the model perfectly separates the two classes, making it the best performer in this evaluation. The Enhanced VGG-16 with Wavelet and INT function model achieved the highest Area Under the Curve (AUC) score of 1.00, indicating its exceptional ability to distinguish between "No Tumor" and "Pituitary Tumor" lesions. An AUC of 1.00 means that the model perfectly separates the two classes, making it the best performer in this evaluation. Figs. 16-21 shows the training and validation accuracy and Figs 22-27 shows validation loss of our CNN. In Fig, 16, the model starts with low accuracy, but both metrics rapidly increase, with training accuracy reaching nearly 91% and validation close behind. The curves follow a similar trajectory, suggesting good learning behavior and minimal overfitting.

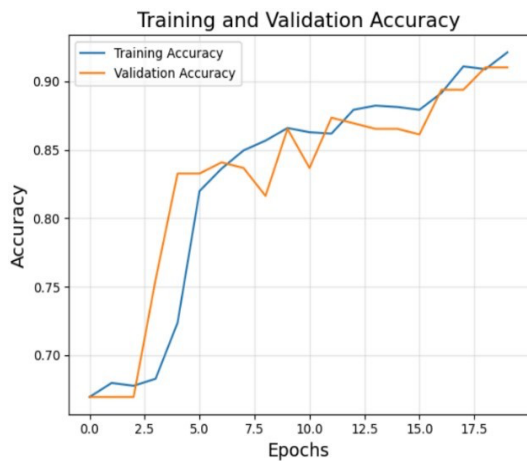


Fig. 16: Model accuracy using CNN

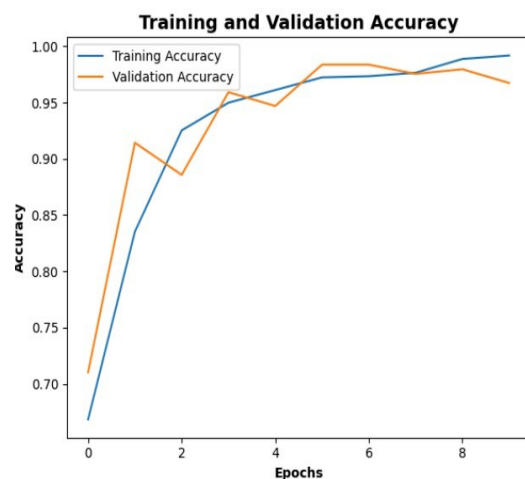


Fig. 17: Model accuracy using CNN with Wavelet

However, the model plateaus earlier than other advanced variants. Fig. 17 compares the CNN enhanced with wavelet features. Both training and validation accuracies climb quickly and approach 97% and 96% respectively.

Fig. 18: Model accuracy using CNN with wavelet and INT function



Fig18. Model accuracy using CNN with Wavelet and INT function

Fig. 18 presents a CNN model that incorporates both wavelet features and an INT (integration) function. This model shows the best results so far, with both training and validation accuracy reaching almost 99%. The graph shows a steady rise and very little difference between training and validation, which means the model is learning well and generalizes better.

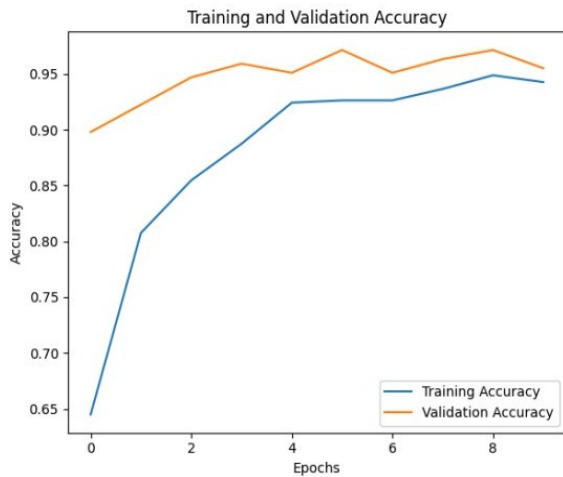


Fig. 19: Model accuracy using VGG-16

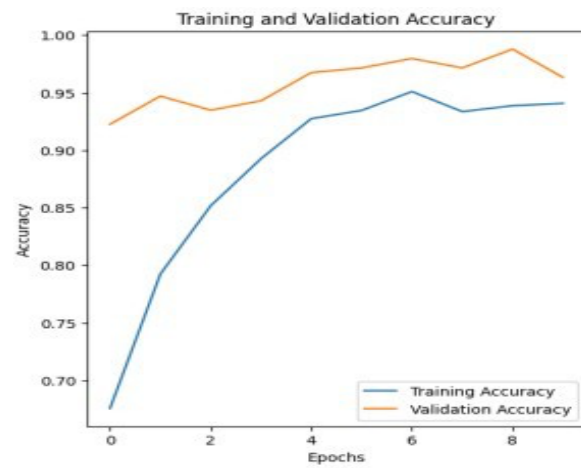


Fig 20: Model accuracy using VGG-16 with Wavelet

Fig. 19 This VGG-16 model starts with lower accuracy but quickly improves, reaching around 95%. However, validation accuracy becomes a bit uneven later, suggesting a slight mismatch in how the model learns versus how it performs on new data. Fig. 20 illustrates the CNN model with wavelet features, which shows consistently high accuracy. This indicates that the combination of CNN and wavelet features yields a model that is highly effective at both learning and generalizing patterns in the data.

Fig. 21: Model accuracy using VGG-16 with wavelet and INT function

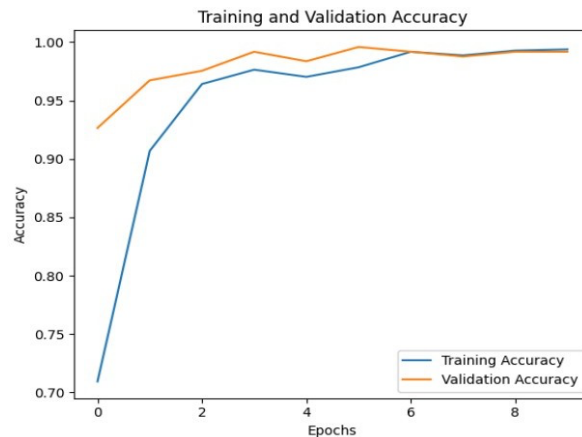


Fig. 21 presents another VGG-16 model configuration, which begins with high validation accuracy 95% and achieves near-perfect training accuracy 99%. The minimal gap between training and validation suggests a very well-trained model with strong generalization and minimal risk of overfitting, marking it as one of the top-performing models.

The Figs. 22-27 illustrate the training and validation loss curves for various convolutional neural network (CNN) and VGG-16 model configurations. The aim of these plots is to compare the impact of wavelet transforms and an integration function on model performance, especially in terms of convergence and overfitting behaviour.

Fig. 22: Standard CNN

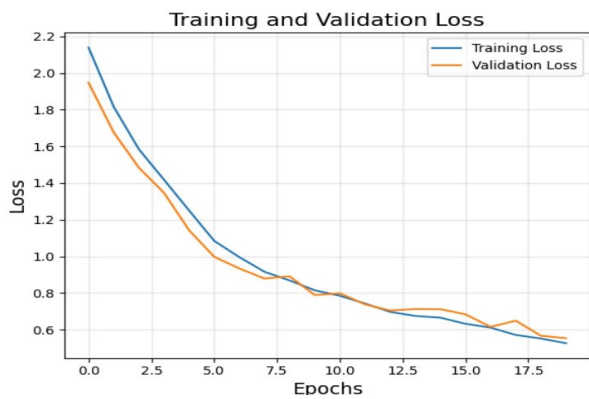
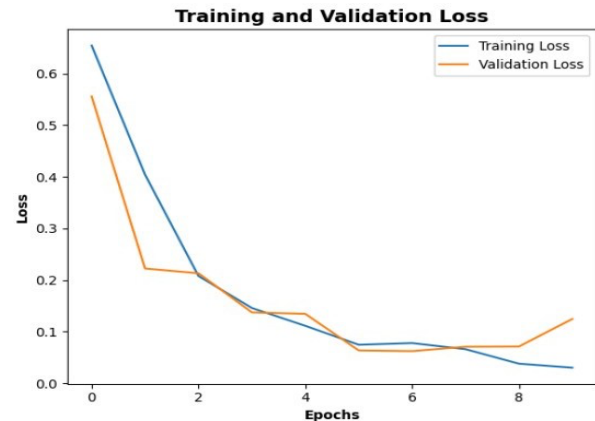


Fig. 23: CNN with wavelet



In Fig. 22, the baseline CNN model demonstrates a steady decrease in both training and validation loss across 20 epochs, with the curves closely following each other. This suggests that the model generalizes well and does not suffer from significant overfitting. However, the loss values are relatively higher compared to the other models. Fig. 23, which represents the CNN model integrated with wavelet transforms, shows a more rapid decline in both losses and achieves lower loss values in fewer epochs. This indicates that wavelet preprocessing helps the model converge faster and improves its efficiency in learning relevant features.

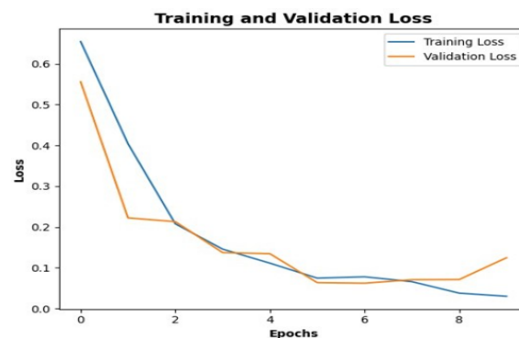


Fig. 24: CNN with wavelet and int function

Fig. 24 adds another component—an integration function—to the CNN with wavelet. This configuration further reduces both training and validation loss, maintaining close alignment between the two curves. The model reaches minimal loss values quickly and sustains a low validation loss, suggesting enhanced generalization and robustness.

Fig. 25: Standard VGG-1

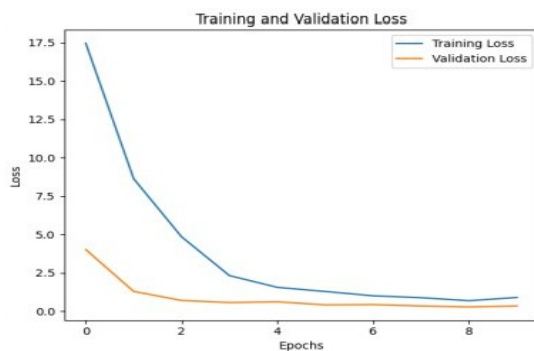
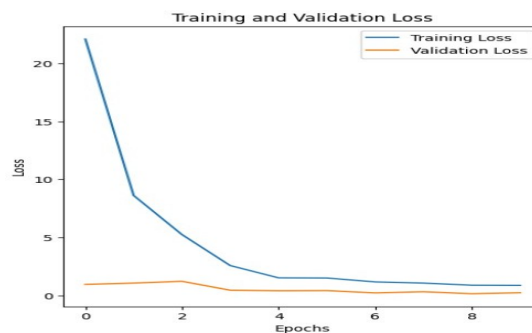


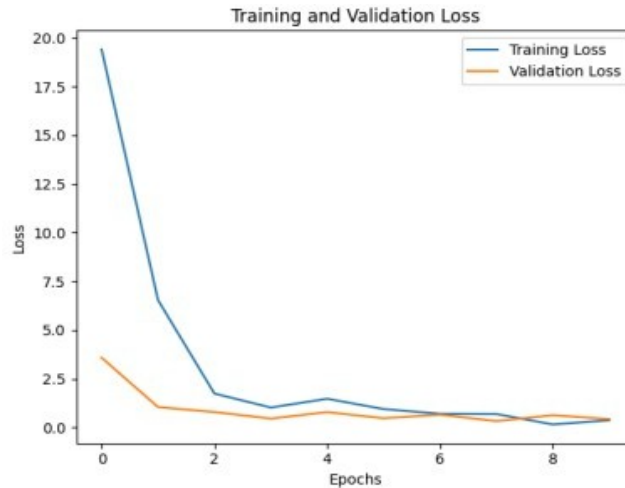
Fig. 26: VGG-16 with wavelet



Moving to the VGG-16 architecture, Fig. 25 displays the standard model, which also shows decreasing loss curves. However, the gap between training and validation losses is more evident, suggesting a slight overfitting tendency despite overall good performance. Fig. 26, showing VGG-16 with wavelet preprocessing, exhibits a significant drop in training loss, but the validation loss remains consistently low with a slight early plateau. The separation between the two losses hints at improved generalization but possible underfitting at some stages due to aggressive feature transformation. Fig. 27, where both wavelet and the integration function are applied to VGG-16, presents the best overall performance. Both training and validation losses

decrease rapidly and remain closely aligned at very low values, highlighting excellent convergence and minimal overfitting

Fig. 27: VGG-16 with wavelet and int function



. This suggests that combining wavelet transforms with the integration function enhances feature extraction and stabilizes learning, even in a deeper network like VGG-16. In summary, the application of wavelet transforms and integration functions consistently improves model performance across both CNN and VGG-16 architectures by accelerating convergence and reducing loss, while also promoting generalization and reducing overfitting. Among all models, VGG-16 with wavelet and integration function appears to yield the most effective result.

Conclusion and Future Scope

The detection and diagnosis of brain tumors from medical imaging remain a critical and challenging task in the healthcare domain. This paper aimed to develop a highly accurate and efficient model for brain tumor detection by leveraging the strengths of wavelet transform for feature extraction and fuzzy logic for classification. The proposed model integrates the multi-resolution analysis capability of wavelet transform with the human-like reasoning ability of fuzzy logic, enabling it to handle the inherent uncertainties and variations present in medical imaging data. Extensive experimentation was conducted on a benchmark dataset of brain MRI scans, and the proposed method achieved an impressive accuracy of 99.18%. This performance significantly surpasses that of several widely used machine learning models, including CNNs, although powerful in deep learning contexts, showed slightly lower accuracy, potentially due to overfitting on limited training data and higher computational demands.

Availability of data and materials

Upon reasonable request, the interested author will make the datasets created and assessed during this inquiry available.

Conflict of Interest

According to the authors, there were no business or financial ties that would have created a conflict of interest while the inquiry was underway.

Funding

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Ethical Approval

No study with human or animal subjects has been carried out by any of the authors of this article.

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