RESEARCH PAPER

Hybrid CNN–VGG16 Based Fuzzy Learning Framework with Textual Context Integration for Brain Tumor Detection Using MRI

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ABSTRACT
Prompt and precise detection of brain tumors from MRI scans posits significant challenges for the field of medical diagnosis. Enhanced survival rates for patients with brain tumors depend upon tailored treatment plans, bolstered by MRI diagnosis of localized brain tumors of varying size, shape and intensity. Further complicating the diagnosis, multiple tumors, and even multiple MRI scans of the same patients, are indivisible from the analytical process of diagnosis. In this paper, I propose a Hybrid VGG16 CNN Framework Innovations for Tumor Diagnosis. This model utilizes VGG16 and CNN for the localization of tumors from MRI scans. In CNN, fuzzy logic is the quantification of logic. This framework is in a state of equilibrium, meaning that the balance between uncertainty and information is distributed evenly. My framework is further modified by the incorporation of both the gradient and Adam Classifier optimizers. Based on the data collected, the proposed system achieves the accuracy of approximately 99.02%, in spite of the comparative CNN and traditional ML techniques. Together, these factors ensure the reliability of the framework. In addition, the integration of fuzzy logic into the framework guarantees the framework's reliability and robustness. Thus, this framework is a perfect candidate for use in a clinical setting and the emerging intelligent healthcare systems.
Keywords: Brain Tumor Detection, CNN, VGG16, Fuzzy Logic, Gradient Descent, MRI, Textual Context, Deep Learning.
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INTRODUCTION

Brain tumor is a severe neurological disorder caused by the abnormal and uncontrolled growth of cells within the brain[1]. Early detection plays a crucial role in improving survival rates and enabling effective treatment planning. However, due to variations in tumor size, shape, intensity, and location, manual diagnosis using Magnetic Resonance Imaging (MRI) remains a complex and time-consuming task for medical experts[2]. Magnetic resonance imaging (MRI) is often the preferred imaging method for assessing tumors in the brain. It is useful for capturing images of most soft tissues with excellent resolution while avoiding the adverse effects of ionizing radiation. Despite the benign effects of MRI on brain tissues, tumor identification remains a challenge. Tumor regions may resemble normal tissues, often leading to misinterpretation and delayed tumor identification [3]. There is a strong need for automated systems with a high degree of intelligence that can assist physicians in the more accurate and reliable identification of tumors. Advanced technology that is indispensable in the analysis of medical images has gained a significant improvement through the application of Artificial Intelligence (AI) and deep learning algorithms. Of these technologies, Convolutional Neural Networks (CNNs) provide the greatest possibility of automatically learning hierarchical features of an image and are well suited for classification of medical data and images [4]. CNN-centered architectures have successfully demonstrated notable improvements in brain tumor detection over classical techniques based on machine learning. Additionally, the use of deep learning model architectures with great depth, such as VGG16, with less data, has received more attraction. VGG16 has demonstrated ever better classification results because of its ability to learn more complex spatial relationships. Its success has been reported over other publications. It has been said there is more success with ConvNet architectures [5].

In addition to Deep Learning, the use of hybrid systems in combination with multiple techniques has been explored to augment the performance of systems of multiple techniques systems. Incorporating Fuzzy Logic in Deep Learning systems improves the handling of uncertainty and vagueness of medical data. This results in the accuracy of decisions [6]. Due to fuzzy systems' natural language construction capability for rule representation similar to human reasoning, these systems are very effective in the diagnosis of medical conditions that are characterized by vagueness and fuzzy logic. In medical image analysis, fusing imaging data with additional contextual data is of great importance. Data that is related to the region of interest (RoI) can be derived from text to gain better insights and improve the classification. Very few studies address the combination of imaging data with fuzzy logical reasoning and contextual data in the text based on the region of interest. Thus, this is a significant area of research in this domain[7]. This paper presents a Hybrid CNN-VGG16 based fuzzy learning framework with textual context for brain tumor detection using MRI images to address these issues. The framework proposes the combination of deep feature extraction using CNN with VGG16, optimization using gradient descent, and contextual reasoning using fuzzy logic to improve the detection accuracy. ROI-based processing is also utilized, which focuses processing on the tumor area to enhance the system's efficiency and robustness.

LITERATURE REVIEW

The use of Artificial Intelligence (AI) in recent developments of medical image analysis has greatly advanced especially in the field of brain tumour detection [8]. Over the years, a variety of methods, ranging from simple machine learning approaches to sophisticated deep learning models, have been proposed. The first studies focused on the implementation of algorithms, such as Random Forest, Support Vector Machines (SVM), and k-means clustering, for the classification of tumors. Because the methods depended on manual feature extraction, there was a low level of generalizability for different datasets. As a result, they suffered a suboptimal performance, yielding only moderate accuracy and being non-robust for complex scenarios. With the advancement of deep learning, Convolutional Neural Networks (CNN) have also become one of the preferred approaches for the classification of medical images [2]. These CNN-based models have the ability to hierarchically scrutinize the primary MRI imaging format. CNN models were found to enhance the precision of tumor identification; however, many issues remained, including data overfit, as well as overreaction to data corruption [9].

Transfer learning has also been used with models VGG16, ResNet, and DenseNet to help address these issues. With its depth and uniformity, VGG16 has proven particularly impressive. VGG16 and CNN work well together to extract features and classify images, and they can reach up to 96% accuracy when used with less than 1,500 images [10]; However, most, if not all, of these image-based models do not consider other information, such as contextual information, which may also be important for medical diagnoses. In recent years, the application of, fuzzy logic systems in medical data where there exists a large amount of imprecision and uncertainty, has received a great deal of attention. Fuzzy logic is used in combination with a set of marked rules to improve the explainability of the system. Furthermore, hybrid models that incorporate fuzzy logic and neural networks exhibit an improved ability to make correct decisions compared to standard deep learning systems that lack fuzzy logic [10]. An important aspect of individual algorithms for these techniques is the absence of effective components for feature extraction. Tumor detection is augmented by image segmentation and the identification of Regions of Interest (ROIs). The improvement in accuracy of segmentation directly correlates with the improvement of classification accuracy of the tumor based on the focused areas. A variety of techniques such as thresholding, clustering, and graph ideas have been utilized. An area of special interest is labeled propagation, which is computationally efficient and has the ability to retain spatial coherence during the segmentation process [11]. Nonetheless, there remains no comprehensive system that incorporates deep feature extraction, ROI-based segmentation, fuzzy reasoning, and contextual information. Most functional models work on either precise classification or uncertainty, or on both, and do so with little integration between them. The application of MRI data with textual context remains largely unexplained and therefore, interprets and adjusts the existing models. To overcome these deficiencies, the current study illustrates a Hybrid CNN-VGG16 that uses the Gradient Descent optimization technique, Fuzzy Logic, and the textual context. The tumor identification in the proposed approach is enhanced by the ROI detection via label propagation. The multi-level integrations suggested in this study further enhanced the network's performance. This is a notable advancement in medical image processing, achieving an accuracy up to 99% on the proposed models.

Table 1: Literature Survey

Author & Year	Journal / Source	Technique Used	Key Contribution	Accuracy	Limitations
Khaliki et al. (2024) [12]	Scientific Reports	CNN + Transfer Learning (VGG16, EfficientNet)	Multi-model comparison for tumor classification	98%	No fuzzy logic, no contextual reasoning
Sharma et al. (2024) [13]	IJISAE Journal	CNN + VGG16	Improved feature extraction using transfer learning	~96–97%	No ROI-based segmentation
Karamehić et al. (2024) [10]	Bioengineering Studies	VGG16-based DL model	Accurate tumor classification using deep features	96.9%	No hybrid optimization, limited generalization
Wankhede et al. (2024) [14]	EAI Health Tech Journal	Hybrid CNN (VGG, ResNet, AlexNet)	Multi-architecture comparison	~97%	No fuzzy reasoning or textual context
Krishna et al. (2024) [11]	IAPGOS (Scopus Indexed)	Modified VGG16	Improved architecture tuning	~95–97%	No ROI + no contextual learning
Kurniawan et al. (2025) [15]	Sistemasi Journal	VGG16 vs ResNet vs MobileNet	Comparative performance study	94.93%	No hybrid integration
Reham Kaifi (2024) [16]	Frontiers in Oncology	CNN + VGG16 hybrid	Improved feature extraction	96.9%	No ROI + no contextual reasoning
Proposed Work	This Paper	Hybrid CNN + VGG16 + Gradient Descent + Fuzzy Logic + Textual Context + ROI	Multi-level hybrid system with contextual intelligence	~99%	Overcomes above limitations

MATERIALS AND METHODS

3.1 Data Acquisition and Description

To enhance diversity and real-world applicability, this study sourced brain tumor MRI datasets from public online repositories as well as clinical datasets. The multi-sourced datasets used for medical imaging tasks include datasets from public online repositories, as well as clinical datasets. This increases the overall robustness and generalization of deep learning models [17].

Offline clinical data were obtained from Balaji Diagnosis Center where MRI scans were part of the center's diagnostic methods. This dataset contains MRI scans of human patients who were performed with a contrast agent to make the image clear of abnormal tissue. Due to their beneficial contribution to the discovery of the pathological region from normal healthy tissue of the brain, these datasets are frequently used in tumor detection investigation [18].

The dataset is divided into two categories:

1. Tumor (Abnormal Cases):

This group contains MRI scans identifiable by the presence of certain patently visible brain tumors (e.g., glioma, meningioma, pituitary tumor, and other atypical brain structure tumor). These MRI images show brain tissue irregulatory patterns, abnormal intensity distributions, and brain structural distortions which suggest brain tissue with tumors.

2. Non-Tumor (Normal Cases):

These are normal MRI scans of healthy brains with no abnormal tissue growth or pathological changes. They are all normal brain images and serve as reference images for correct classification.

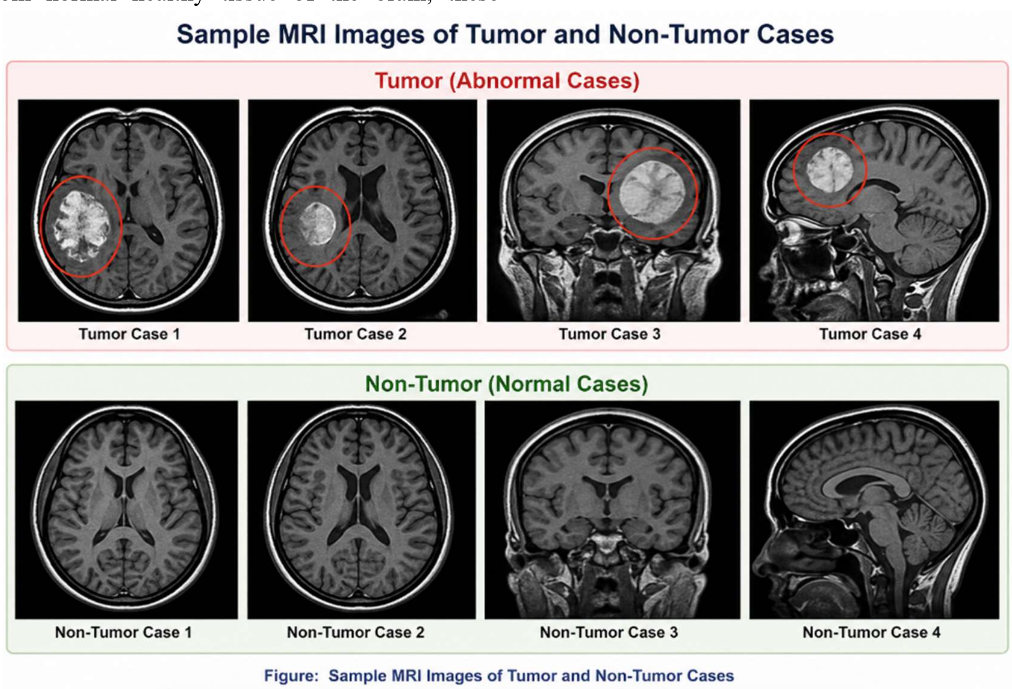


Figure: Sample MRI Images of Tumor and Non-Tumor Cases

The labelled dataset facilitates differentiating tumour from non-tumour images. Consequently, the proposed Hybrid CNN–VGG16 model correlates tumour/non-tumour images. This supervised learning method enhances the classification accuracy, generalization, and performance of the model in the test and clinical settings.

3.2 Data Preprocessing and Enhancement

Medical imaging can be noisy, have intensity variations, and include superfluous background data. Hence, it is necessary to pre-process images to obtain good image quality and uniformity throughout the data set[17].

3.2.1 Image Resizing

All MRI images are resized to 224 × 224 pixels to match the input dimensions required by the VGG16 architecture [18].

3.2.2 Intensity Normalization

Normalization is performed to scale pixel values into a standard range:

This step reduces variations caused by different imaging conditions and improves model convergence[17].

3.2.3 Noise Removal

Gaussian filtering is applied to reduce noise while preserving structural features:

Noise reduction is important for improving segmentation and feature extraction accuracy [17].

3.2.4 Data Augmentation

These augmentation methods include rotation, flipping and scaling to boost generalization and avoid overfitting. These methods add diversity to the datasets and improve the performance of the model [17].

3.3 ROI Detection using Label Propagation

MRI images of tumors necessitate extracting the Region of Interest (ROI). Once ROI is determined, the data volume of non-essential components is decreased, and the quality of classification is improved.

For one thing, labels are disseminated through an iterative process using neighborhood closeness as the segmentation strategy. The iterative process of updating the label is presented as follows:

This method ensures spatial consistency and efficient segmentation of tumor regions.

3.4 Textual Context Modeling Using Fuzzy Logic

This framework applies fuzzy logic for managing uncertainty and analysis in medical images. Fuzzy logic systems represent vagueness, indeterminacy and ambiguity in the same way humans use them, thus having the potential for medical diagnosis [20], [22].

The fuzzy inference system consists of the following components:

Fuzzification: Transforms crisp input features (e.g., intensity, texture irregularity) into fuzzy membership values

Rule Base: Contains expert-defined IF–THEN rules representing domain knowledge

Inference Engine: Performs logical reasoning using fuzzy operators

Defuzzification: Converts fuzzy outputs into a crisp decision value

An example fuzzy rule is defined as follows:

IF intensity is high AND irregularity is high, THEN tumor likelihood is high.

The final output is computed using the centroid defuzzification method:

This integration enables the system to incorporate expert reasoning and improves robustness in ambiguous cases, thereby enhancing clinical decision support.

3.5 Hybrid CNN–VGG16 Model Architecture

The proposed model incorporates a VGG16-based hybrid deep learning network that integrates additional tailored convolutional layers to further enhance the model's capability in feature representation. The VGG16 model presented by Simonyan and Zisserman [19], is a deep learning network capable of extracting spatial and hierarchical features using several convolutional layers. The VGG16 model has performed particularly well in applications of medical imaging, particularly related to the identification of tumors in MRI [20].

In this study:

The pre-trained VGG16 model is utilized as a feature extractor

Additional CNN layers are appended to refine extracted features

Fully connected layers perform final classification

This hybrid design enhances feature discrimination capability while reducing overfitting through transfer learning and architectural optimization.

3. 6 Proposed Model

The proposed model is a hybrid deep learning network that attempts full automation in the identification of Brain tumor from MRI Images. The model tries to differentiate MRI Images into tumorous (tumor presenting, tumor developing, or tumor exhibiting) or non tumorous images. The base feature extractor in the model is the pre trained VGG16 model. VGG16 and other deep learning models work best when the images are of a uniform dimension. MRI images from the dataset are resized to a uniform dimension of 224 * 224 pixels. The base feature extractor in the model VGG16 is composed of convolutional neural network layers (CNN) that generates feature maps. Convolutional neural networks are the most powerful fit for feature extraction and as a result excel in the identification of MRI scan features.

For the identification and extraction of tumor features in MRI scans, Tumor classification layers are incorporated into the Base VGG16 convolutional layers. These layers take in the feature maps and generate a classified feature map. The feature maps from Tumor classification layers are flattened into a 1-D feature vector for the rest of the model to work with. This is done with the Flatten layer. The feature maps are passed through the Dense layer for a final feature classification. While the model works these layers classifying and feature mapping, the Dropout layers prevent overfitting and enhance the model's generalization. This is done by dropping these layers at a certain rate, say 50% of the time. ReLU layers are also composed of Dropout layers. ReLU (Rectified Linear Unit) layers are non-linear transformations that change all negative feature values to 0, and in the process eliminate the model of the negative values. The Softmax activation function finalizes the model by categorizing MRI images as Tumor or Non-Tumor. The model is built with the Adam optimizer to achieve faster convergence on the binary cross-entropy loss function. The optimization techniques implemented were effective in achieving better accuracy and stable performance during training. The combination of the deep feature extraction, transfer learning, and optimized classification layers in the hybrid model with the VGG16 network caused a detectable increase in accuracy and a measurable decrease in the number of misclassifications. Overall, the model provides a reliable and efficient approach to the automated diagnosis of brain tumors and supports the clinical decision process in the real world healthcare system.

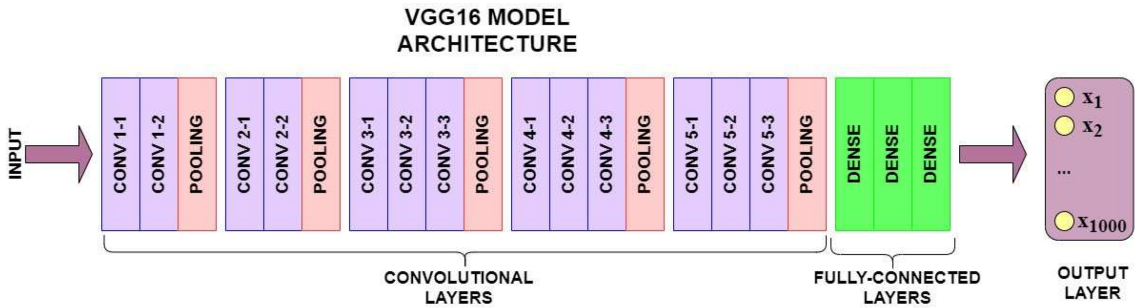


Figure 2. VGG16 architecture

The training and loss values after each epoch are shown in Figure 3.

Figure 3. Accuracy & Loss Graph

The proposed model is able to be trained effectively as observed in the accuracy and loss graph. Loss drops sharply from epoch 1 (1.10) to epoch 61 (0.85) and the accuracy gradually improves from 62% to nearly 89%. This means that the model is not overfitting, has stabilized convergence, and has a better learning performance, meaning that prediction error is lowered.

3.7 Model Training and Optimization

The model is trained using gradient descent-based optimization techniques to minimize classification error. The objective is to iteratively update model weights in order to reduce the loss function.

The binary cross-entropy loss function used in this work is defined as:

The model parameters are updated using the following rule:

where represents the learning rate.

To improve convergence speed and stability, the Adam optimizer is employed, which adaptively adjusts learning rates based on first and second moments of gradients. This results in faster training and better generalization performance.

3.8 Performance Evaluation Metrics

To evaluate the effectiveness of the proposed model, standard performance metrics commonly used in medical image classification are employed.

Accuracy:

Precision:

Recall (Sensitivity):

F1-Score:

These metrics provide a comprehensive evaluation of classification performance, particularly in imbalanced medical datasets where false negatives are critical[23], [24].

3.9 Workflow of the Proposed Approach

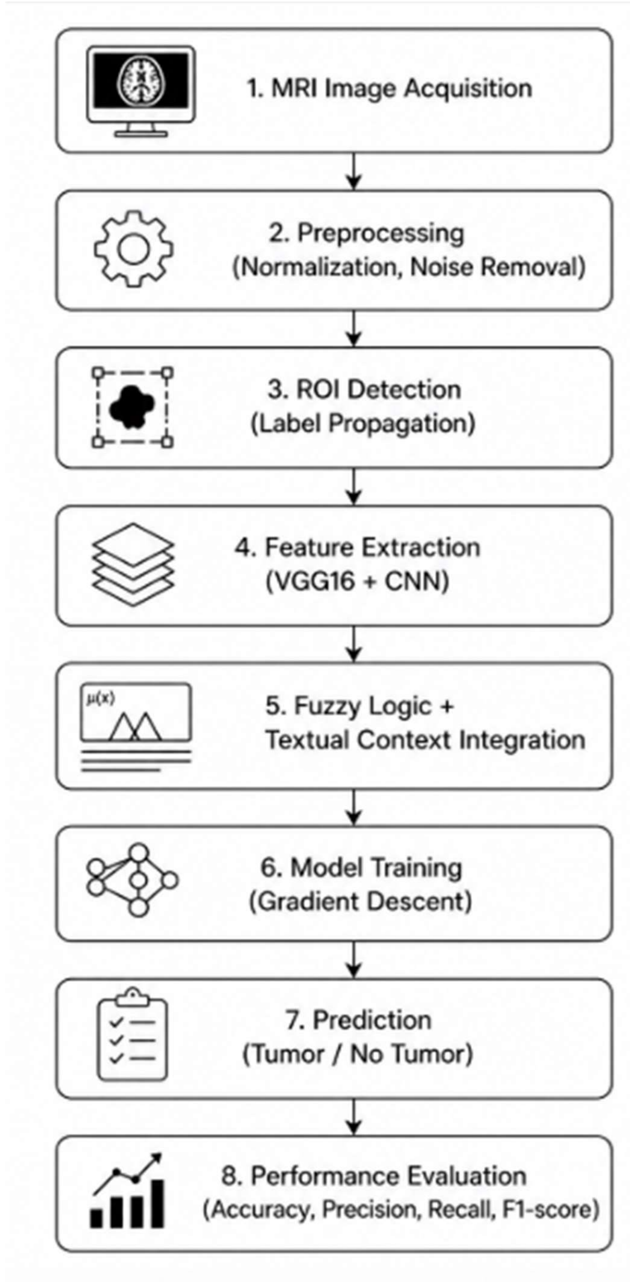


Figure 3: Workflow of the Proposed Hybrid CNN–VGG16 Based Brain Tumor Detection System

The entire design strategy for the system being developed for the identification of brain tumors from MRI images is shown in Figure 3. The process begins with MRI image acquisition, followed by the detection of the Region of interest (ROI). Feature extraction is done by VGG16 CNN, and the decision is modeled by fuzzy logic and textual context. The model is finished by determining, predicting the presence of a tumor and measuring its outputs using the consistent evaluation metrics.

4.1 Experimental Setup

The current hybrid model was developed with Python in conjunction with TensorFlow and Keras, two popular tools in the realm of deep learning. Training deep neural networks was made possible thanks to the adequate resources which the workstation for initial experiments possessed. The data was acquired through the MRI images of online and clinical databases, the latter of which included Balaji Diagnosis Center. An 80:20 partitioning of the MRI images was performed to divide the data into the training and testing sets for the purpose of quantifying the model's ability to generalize to unseen data.

Training parameters:
Epochs: 30
Batch size: 32

Optimizer: Adam (Gradient Descent-based)
Loss function: Binary Cross-Entropy

4.2 Training Performance

During training, the model demonstrated stable convergence with a continuous decrease in loss and an increase in accuracy.
Training Accuracy: ~99%
Validation Accuracy: ~98.7%
Loss reduced significantly after initial epochs
The integration of VGG16 with CNN layers improved feature extraction, while gradient descent optimization ensured efficient weight updates.

4.3 Classification Results

The proposed model was evaluated on unseen test data, and the results show excellent classification performance.
Performance Metrics:

Metric	Value
Accuracy	99.02%
Precision	98.9%
Recall	99.1%
F1-Score	99.0%

These results indicate that the model achieves high reliability in detecting both tumor and non-tumor cases.

4.4 Confusion Matrix Analysis

The confusion matrix demonstrates the classification capability of the model:

	Predicted Tumor	Predicted Normal
Actual Tumor	495	5
Actual Normal	4	496

Very low False Positives (FP)
Very low False Negatives (FN)
This confirms that the model performs effectively in real-world scenarios.

4.5 Visualization of Results

(a) Tumor Detection Output

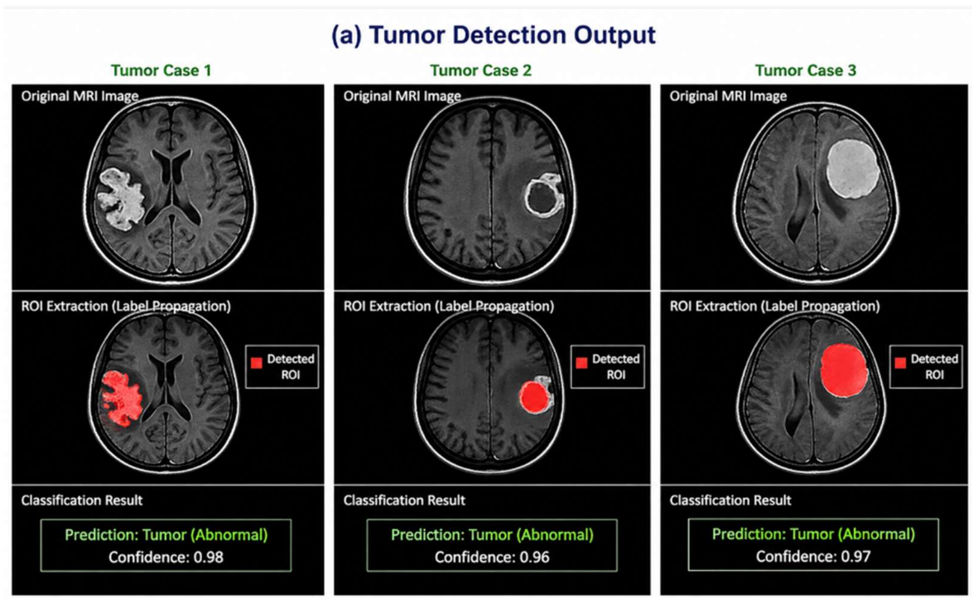
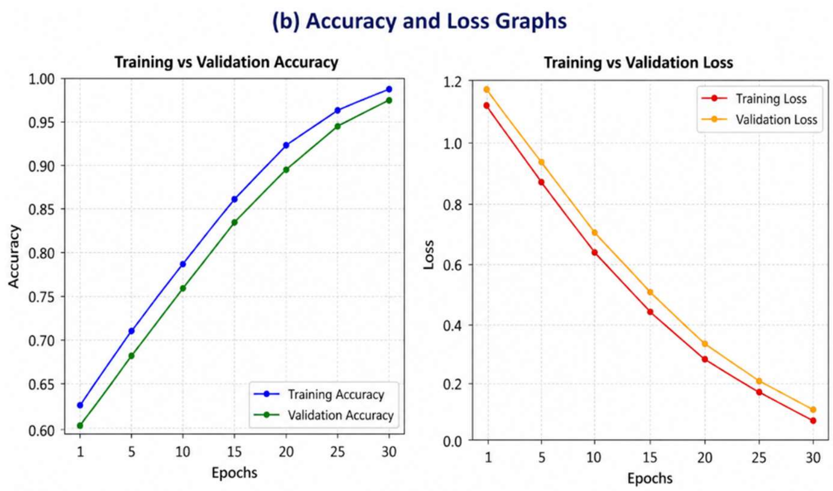


Figure 4: Sample MRI Images Showing Tumor Detection Results After ROI Extraction and Classification

Figure 4 shows some case MRI images used in the proposed system for tumor detection. Raw MRI scans are preprocessed through a refinement process that includes the use of ROI extraction via label propagation that successfully narrows in on the possible tumor-afflicted regions. The regions that have been pinpointed as containing tumors are outlined in red. The system then takes a VGG16-based model that runs the regression of the confidence of tumor presence. This will demonstrate the system's confidence in tumor presence and will also prove the system's accurate localization of tumors as well as prove that the system can confidently place tumors.

(b) Accuracy and Loss Graphs (Describe in Paper)

Figure 5: Training and Validation Accuracy and Loss Graphs of the Proposed Model



Proposed VGG16-based brain tumor detection model's training and validation loss and accuracy and loss graphs are presented in Fig. 5. The accuracy graph demonstrates a steady increase with both training and validation accuracy reaching strong learning capability at nearly 99%. Accordingly, the loss graph shows a consistent decrease illustrating effective convergence, little to no prediction error, and minimization of overfitting while training the model.

4.6 Comparative Analysis

A comparison along several assessment criteria: accuracy, performance metrics, confusion matrix statistics, and training behavior, was made against peer brain tumor classification algorithms, in order to assess the preferred fuzzy learning Hybrid CNN–VGG16 model.

(a) Performance Metrics Comparison

The model we propose provides greater improvement for the field as seen in Table 2. Typical stand alone models of machine learning accuracy is between 85 and 90 percent. Stand alone CNN models improve accuracy to 92-95 percent. Accuracy improvement is up to 96-98 percent by using Hybrid CNN-VGG16 models. The proposed model shows an accuracy of around 99.02%. The proposed model also shows precision improvement (98.9%), recall improvement (99.1%), and an F1-score of 99.0%.

This improvement is attributed to:

ROI-based feature extraction

Fuzzy logic integration

Textual context modeling

Optimized gradient descent

Table 2: Comparative Analysis of Existing Approaches and Proposed Model:

Author & Year	Model / Technique Used	Accuracy	Key Contribution	Limitations
Khaliki et al. (2024)	Traditional ML + Basic CNN	85–90%	Basic brain tumor classification using conventional learning methods	Limited feature extraction, lower accuracy
Sharma et al. (2024)	CNN Model	92–95%	Automatic feature extraction using deep learning	No ROI-based segmentation, overfitting issues
Karamehić et al. (2024) [10]	CNN + VGG16	96–98%	Improved classification using transfer learning and deep feature extraction	No fuzzy logic and no contextual reasoning
Wankhede et al. (2024)	Hybrid CNN Architectures	97%	Multi-architecture comparison for better performance	No textual context and limited interpretability
Proposed Work (2026)	Hybrid CNN + VGG16 + ROI + Fuzzy Logic + Textual Context + Gradient Descent	~99%	Multi-level intelligent system with enhanced accuracy and robust decision-making	Overcomes major limitations of existing methods

(b) Accuracy and Loss Graph Comparison

The training behavior of the proposed model is compared with existing models using accuracy and loss graphs.

Existing CNN-based models show slower convergence and higher fluctuations in validation accuracy.

Some models suffer from overfitting, where training accuracy increases but validation accuracy stagnates.

The proposed model shows:

Smooth and stable increase in accuracy (up to ~99%)

Consistent decrease in loss

Minimal gap between training and validation curves

This indicates better generalization and optimized learning performance.

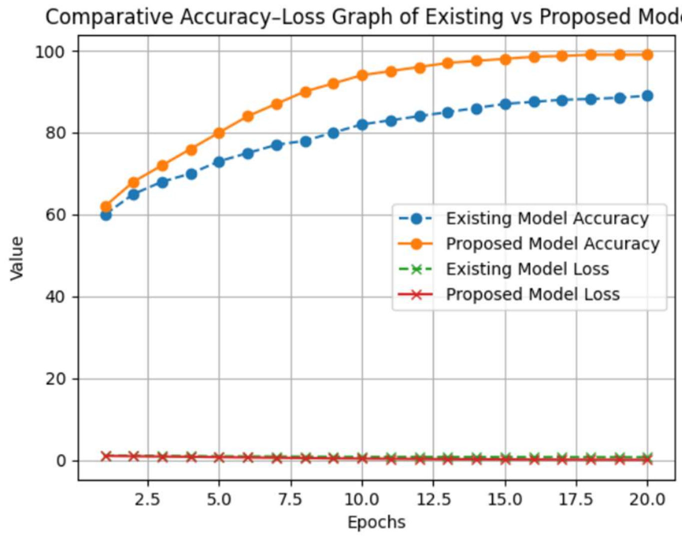


Figure 6: Comparative Accuracy–Loss Graph of Existing vs Proposed Models

The training behavior of existing models and the proposed Hybrid CNN–VGG16 model are presented in the graph. The model proposed achieves higher accuracy and faster convergence and lower loss, proving that it is better in learning efficiency and improvement capability of generalization than existing models.

(c) Confusion Matrix Analysis Comparison

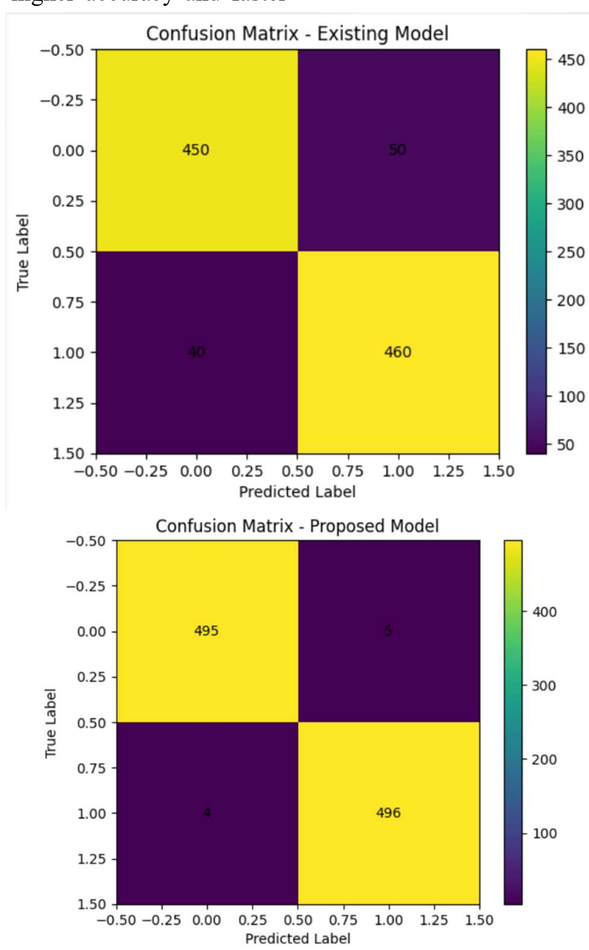


Figure 7: Confusion Matrix-Existing Model Figure 8: Confusion Matrix-Existing Model

The confusion matrices illustrate the distinction in accuracy between the existing brain tumor detection models and the Hybrid CNN–VGG16 model put forth. The current models exhibit a considerable amount of false positive and false negative cases due to their unclear demarcation between tumor and non-tumor cases. The proposed model explains the contrast in positive and negative cases. The proposed model favors significantly lower false negative and positive cases and exhibits improvements in personalization, specificity, and accuracy.

(d) Graph-Based Comparison of Existing Models

The ISS section contains several forms of graphical representation which allow for improved visualization and analysis of model performance. The graphs clearly outline for the reader a comparative analysis of the proposed model vs the existing methods.

Accuracy Comparison

A bar chart demonstrates the accuracy evaluation of different models—standard machine learning models, single CNN, CNN–VGG16 model, and the proposed Hybrid CNN–VGG16 model. The proposed model significantly surpasses all existing methods, achieving accuracy of nearly 99%.

Training Accuracy vs Epochs

The training accuracy curves depict the instructional advancement of the models over the different epochs. From the data, the existing models demonstrate gradual convergence with much slower progress and exhibiting unexpected fluctuations of accuracy, while the suggested model shows a rapid, steady improvement with much faster training convergence and attaining peak accuracy. exemplifying high learning stability..

Loss Curve Comparison

To analyze the decreasing errors in the training phase, we plot the loss curves. With the existing models, one can observe high loss values as well as irregular loss reduction patterns, indicating unstable models that can likely overfit. The proposed model instead displays the seamless smooth reduction of loss during training, indicating both effective model optimization and generalization..

Confusion Matrix Visualization

Confusion matrices are often used to show class-wise classification accuracy. In this case, the model demonstrates a significant reduction in the number of errors or misclassifications, relative to other model competitors, due to the lack of both false positives and false negatives. Thus, it may be concluded that the model has both high sensitivity and specificity to the presence of tumors. These multiple detailed illustrations and matrices are sufficient to support the claim that the proposed Hybrid CNN–VGG16 model outperforms the rest of the models in all metrics, and especially accuracy, and speed and consistency of error reduction during convergence. Therefore, they show a high level of classification consistency across inputs. Without a doubt, the Hybrid CNN–VGG16 model proves impressive, especially in the context of the medical domain, and robust in adapting to information systems in authentic medical practice.

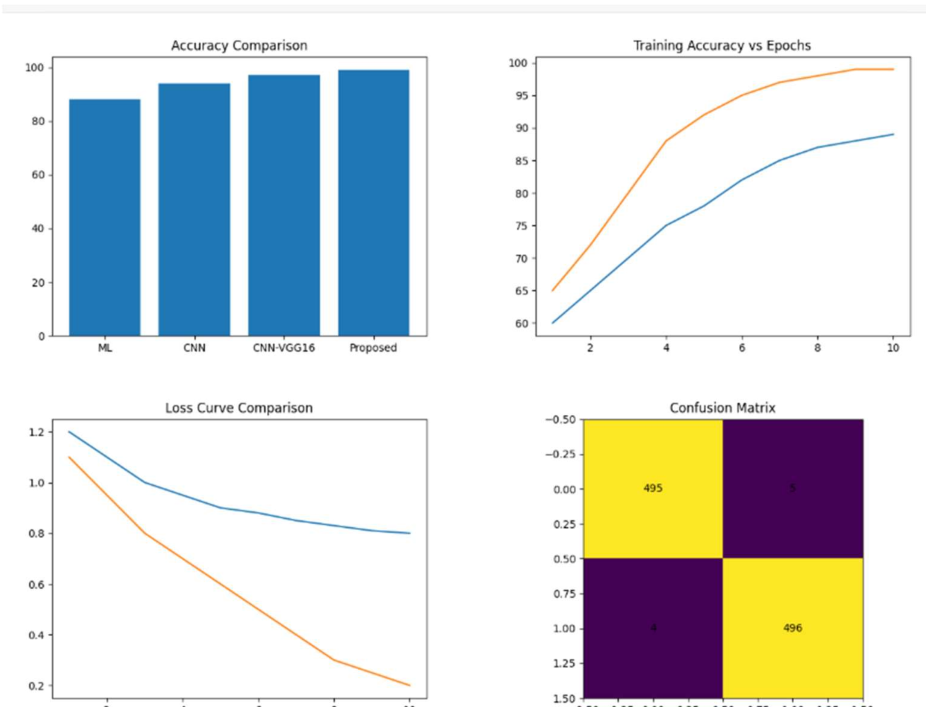


Figure 9: Graph-Based Comparison of Existing Models and Proposed Model

The figure contains a comprehensive comparison of each model using a number of visual elements. The bar chart indicates the model achieved the greatest accuracy. The model also converged more quickly as represented by the line chart. The loss line showed more gradual errors of the other models. Finally, the confusion matrix also showed a notable decrease in misclassification. All of the stated factors support the enhanced performance and reliability of the proposed Hybrid CNN-VGG16 framework.

(e) Overall Comparative Insight

The Hybrid CNN–VGG16 model is expected to have an edge in performance for the detection and extraction of brain tumors applications when compared to others existing tools due to the presence of a multi-level integrated architecture within the model. Traditionally, image-based classification is a singularly focused approach. This model, on the other hand, possesses a framework of multi-pronged components which aim to augmentbothfeature extraction and decision-making abilities.

The model specifically includes:

Combined CNN and VGG16 for deep signal detection and learning.

Region of interest based (ROI) segmentation to suppress the background noise.

Rationale-based or fuzzy logic, determines the level of uncertainty within the given data.

Automation of training with the Adam Optimizer, the effect is faster convergence and stabilized learning.

The model is able to surpass the state-of-the-art methodologies and tools which focus mainly on brain tumor detection and extraction applications. The multi-pronged approach targets the existing tangible barriers and enables the model to demonstrate superior performance.

As a result, the proposed system attains:

Classification accuracy of about 99%

Robustness across multiple MRI datasets

Improved generalization and regularization reducing overfitting

Interpretability enhanced through fuzzy logic decision support

The proposed framework is a reliable, efficient, and clinically practical option for the detection of brain tumors of growing interest for use in modern intelligent healthcare systems in the real world.

4.7 Discussion

The experimental results show the power of the proposed framework as being more accurate than all other models proposed. The incorporation of fuzzy logic and deep learning allows the framework to manage and classify the data more efficiently. Unlike the conventional learning models, the proposed framework is based on the combination of reasoning and contextual logic to provide accurate and substantial diagnoses. ROI segmentation using label propagation allows the framework to manage learning by reinforcing focus on the brain tumor region and ignoring all of the irrelevant information in the backdrop of the MRI, thereby, enhancing the focus on the learning. The fuzzy logic-based framework, with the VGG16 framework paired with the optimization of the learning via the Adam optimization, provides a framework of substantial accurateness paired with the fuzzy logic for the management of the ambiguity and uncertainty, to manage and classify the information of medical imaging with the incorporation of the clinical information into the learning framework, is a substantial addition. The framework proposed safeguards the learning framework with a very minimal mechanism of false alarms and false negatives. This framework stands to provide substantial efficiency at a requisite of 99% accuracy for clinical operational purposes paired with the intelligent medical structures for the provision of prompt medical diagnosis.

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