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A Hybrid CNN and Fuzzy Logic Framework for Enhanced Brain Tumor Detection and Textual Contextualization

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KEYWORDS

Brain Tumors (BT), Early Diagnosis, Deep Learning, Convolutional Neural Networks (CNN), VGG16, Fuzzy Logic Systems, MRI Imaging, Tumor Classification, Feature Extraction, Tumor Size Detection.

ABSTRACT:

One of the most dangerous diseases is brain tumors (BT), which must be identified early and accurately in order to be effectively treated. The manual tumor tagging and image processing used in current diagnosis techniques are labor-intensive and error-prone. In order to overcome these limitations and increase the accuracy of brain tumor identification, this research proposes a hybrid approach that combines deep learning techniques such as convolutional neural networks (CNNs) and VGG versions, fuzzy logic systems, and MRI imaging. This work investigates tumor classification using deep learning and fuzzy logic. Features like tumor size and global threshold values were retrieved from the pre-processed pictures. Tumor size was measured using the watershed and region-growing approaches, and the results, along with the threshold values, were inputs to the fuzzy system. According to experimental data, the fuzzy system achieves good classification accuracy, with CNN + VGG16 models reaching up to 99%, especially when using the region-growing technique for tumor size detection and deep learning feature extraction. This hybrid fuzzy-CNN method shows promise as an effective and precise automated classification system by offering improved region-of-interest (ROI) segmentation and reliable feature identification. This approach may facilitate prompt and accurate clinical decision-making, advancing medical imaging analysis and improving patient outcomes by lowering the need for human involvement.

INTRODUCTION

One of the main causes of mortality and disability in the globe is brain tumors. Since prompt care may greatly increase survival rates and quality of life, early identification is essential for improving patient outcomes. A popular non-invasive imaging method that offers comprehensive anatomical details about the brain and is essential for the detection of brain malignancies is magnetic resonance imaging (MRI) [1]. However, manual MRI scan interpretation is subjective, time-consuming, and prone to human error, particularly when it comes to identifying microscopic lesions or subtle tumor signs. In order to reduce human involvement and improve diagnostic reliability, automated methods that can precisely identify and categorize brain cancers using MRI data are now required [2]. In the field of medical image analysis, Convolutional Neural Networks (CNNs), a subclass of deep learning models, have shown impressive results. CNNs are very successful at tasks like object identification and image classification because of their exceptional ability to extract spatial characteristics from pictures [3]. CNNs have specifically been used to categorize MRI images into tumor-present and tumor-absent groups in the context of brain tumor identification. However, the majority of conventional CNN-based methods mainly use the images' raw pixel data, which may

leave out crucial contextual details like the patient's age, gender, medical history, and other lifestyle factors that could offer important insights into the characteristics and risk profiles of tumors [4]. In order to improve brain tumor diagnosis, this study attempts to get over this restriction by creating a hybrid framework that blends fuzzy logic with CNN-based image processing. In order to increase classification accuracy and provide a more comprehensive picture of the patient's state, the suggested model combines both image-based data (from MRI scans) and extra textual context (patient demographics and medical information). Fuzzy logic integration enables the system to provide both tumor forecasts and human-readable textual descriptions, giving doctors important interpretative context [5].

Three thousand MRI scans, 1,500 of which had tumors and 1,500 of which did not, make up the dataset utilized in this investigation. To make sure they are prepared for input into the deep learning models, these photos go through a number of preparation procedures, including resizing, data augmentation, and image segmentation [6]. Using image segmentation algorithms, the preprocessing also entails the detection and extraction of Regions of Interest (ROIs), particularly the tumor regions. By directing the model's attention to pertinent areas of the pictures, this segmentation phase enhances detection precision and computational effectiveness [7]. In order to capitalize on the advantages of each model for more reliable feature extraction and classification, the hybrid model in this work integrates a number of potent deep learning architectures, such as CNN, VGG16, Efficient Net, and Support Vector Machines (SVM) [8]. In order to improve training and lower computing complexity, transfer learning is used to refine previously taught models. To improve the interpretability of the data, fuzzy logic is also included into the model to evaluate and provide textual descriptions pertaining to the tumor's size, shape, intensity, and other characteristics. The algorithm may, for example, provide textual outputs such as "Medium-sized tumor detected in the left hemisphere," which might help physicians decide on the best course of action [9]. Fuzzy logic-based textual contextualization, hybrid CNN models, and picture segmentation are all used in the suggested approach to increase the precision and interpretability of brain tumor identification [10]. In order to determine how well different hybrid model configurations such as CNN + VGG16, VGG16 + SVM, CNN + EfficientNet, and others distinguish between tumor and non-tumor instances, the research tests them. The findings show that in terms of classification accuracy and diagnostic usefulness, the suggested hybrid framework in particular, the CNN + VGG16 model performs better than conventional techniques [11].

1. LITERATURE REVIEW

The McBee, et.al (2018), [12] discussed the procedures required for a DL project in radiography and looked at the clinical uses of DL in this field. The possible therapeutic uses of DL in different medical specialties were also covered. Although DL has shown encouraging results in a few radiology applications, the technology is not yet advanced enough to take the role of a radiologist in the diagnostic field.[13]. It's possible that radiologists and DL algorithms will work together to improve the efficacy and efficiency of diagnosis. The potential of MRI to detect and categorize brain cancers has been the subject of several investigations using a range of research techniques. In order to boost effort, outperform earlier methods, and obtain a classification rate of 90.89%, Afshar et al. (2019) created a modified version of the CapsNet architecture for classifying the main brain tumor consisting of 3064 pictures utilizing tumor borders as extra inputs.[14]. Gumaei et al. (2019) It's possible that radiologists and DL algorithms will work together to improve the efficacy and efficiency of diagnosis. The potential of MRI to detect and categorize brain cancers has been the subject of several investigations using a range of research techniques. In order to boost effort, outperform earlier methods, and obtain a classification rate of 90.89%, Afshar et al. (2019) created a modified version of the CapsNet architecture for classifying the main brain tumor consisting of 3064 pictures utilizing tumor borders as extra inputs[15].

Matia Martucci et.al (2023), reviews the role of conventional and advanced MRI methods in assessing adult primary brain tumors, emphasizing the integration of these techniques. Future perspectives, including radionics and artificial intelligence, are also discussed, highlighting their potential to improve clinical outcomes in brain tumor management. MRI is essential for brain tumor imaging, significantly impacting diagnosis, therapy planning, and treatment monitoring. It captures both morphologic and non-morphologic characteristics, such as functional, metabolic, and genetic features, enhancing diagnostic accuracy. Understanding the strengths and limitations of various MRI techniques is vital for effective interpretation and optimal treatment strategies[16]. **Mahmoud Khaled Abd-Ellah et.al (2019),** highlights the major accomplishments that are represented in the performance metrics of the algorithms used in the three diagnostic procedures. The effectiveness of therapy and, therefore, patient survival are greatly enhanced by the timely and accurate detection of brain tumors. It is challenging to manually assess the many magnetic resonance imaging (MRI) pictures that are often generated in the clinic. Therefore, computer-aided techniques that are more accurate are essential for early tumor detection. Tumor identification, segmentation, and classification procedures include computer-aided brain tumor diagnosis using MRI images. Traditional or classical machine learning approaches for brain tumor diagnosis have been the subject of several research in recent years. Recently, there has been interest in using deep learning methods to more accurately and robustly diagnose brain cancers [17]. **Deepika Joshi et.al (2017),** evaluations 30 studies investigating tumor detection techniques incorporating picture segmentation were published between 2000 and 2015. picture restoration and picture enhancement are the two main topics of the review. Numerous algorithms and approaches were found, and their advantages, disadvantages, and potential for advancement were examined. The results provide light on the status of brain tumor detection methods today and suggest possible directions for future study and development [18].

2. Basic Architecture of CNN-Based Methods

Sarmad Maqsood et.al (2021), suggests a technique for detecting brain tumors that makes use of U-NET Convolutional Neural Network (CNN) classification and fuzzy logic based on edge detection. Fuzzy logic-based edge detection, classification, and picture enhancement form the foundation of the suggested tumor segmentation system. Dual tree-complex wavelet transform (DTCWT) is used at various scale levels after the input pictures have been pre-processed utilizing contrast enhancement and fuzzy logic-based edge detection to find the edge in the source images. U-NET CNN classification, which distinguishes between meningioma and non-meningioma brain pictures, is used to classify the features that are computed from the decaying subband images [20]. **Kadry S. et al. (2021)** suggested a hybrid deep learning method that uses the ISLES2015 and BRATS2015 datasets to classify brain tumors. For the experimental findings, they used DLS techniques include ResNet50, VGG16, and VGG19. Multi-class classifications were then created using classifiers like Soft Max, SVM-RBF, and SVM-Cubic. Their results showed that, in comparison to other techniques, With SVM-Cubic, VGG19 achieved a much higher accuracy of 96% [21]. **Irmak et al. (2021)** presented three different convolutional network designs for the classification of brain tumors, with the first model obtaining a 99.33% accuracy rate. The second model identified five kinds of tumors: normal, meningioma, glioma, metastatic, & pituitary, with an accuracy of around 92.66%. The third model successfully classified tumors into Grade II, Grade III, & Grade IV with an accuracy of 98.14%. The performance of these proposed CNN models was compared to state-of-the-art algorithms including Inceptionv3, Alex Net, ResNet-50, Google Net, as well as VGG-16. Grid search optimization was used to automatically determine key model parameters. The study utilized publicly released clinical datasets, yielding favorable detection results [22].

Journal of Chemical Health Risks
www.jchr.org
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3. *Hybrid CNN and Fuzzy Logic Approaches for Enhanced Detection and Classification of Brain Tumors*

Seetha and Raja [23] presented a technique for classifying convolutional neural networks (CNNs) with the goal of identifying brain cancers. Deeper in nature, the suggested design uses smaller kernels and has relatively lighter neurons. According to experimental findings, the suggested CNN model showed a 97.5% accuracy rate. Hossain et al. [24] recommended using 2D Magnetic Resonance Brain Images (MRI) to remove brain tumors using the Fuzzy C-Means clustering approach. Convolutional neural networks and conventional classifications replaced this method. Although the suggested use of CNN achieved an accuracy rate of 97.87%, it was observed to necessitate a longer execution time and larger data storage. Toğaçar et al. [25] suggested a new CNN model called Brain MRNet that combines attention modules and a residual network built using hypercolumn technology. Image preparation is the first stage of Brain MRNet, and then image augmentation methods are used. The convolution layer receives the picture once attention modules have chosen the most important portions. Using easily accessible MR scans, the Brain MRNet model was used to identify brain tumors, with a 96.05% classification accuracy. Van Hai and Amaechi [26] suggested a model for the categorization and detection of medical imaging, including the distinction between healthy and cancerous brain cells, that mixes convolutional neural networks with fuzzy rules. The suggested model's experimental findings showed a 97.6% accuracy rate. Lamrani et al. [27] investigated a CNN architecture that was presented for the purpose of classifying MRI brain pictures into two groups: those with and without tumors. Before CNN processing, these medical photos were preprocessed and resized. The pretrained architecture model obtained 96% classification accuracy and precision rates based on training and testing results.

4. Textual Context Generation from MRI Scans

Kyuri Kim et.al (2012), addresses the challenges posed by multi-modality concerns by introducing a framework for text-conditional magnetic resonance (MR) image creation. A diffusion-based prompt-conditional picture creation architecture, a pre-trained big language model, and an extra denoising network for input structural binary masks make up the framework. The suggested framework may produce realistic, high-resolution, and high-fidelity multi-modal MR pictures that correspond with medical language text prompts, according to experimental findings. Additionally, the research uses text-conditional statements to understand the cross-attention maps of the collected data [28].

Medical imaging plays a crucial role in clinical diagnosis and treatment, yet report-writing can be error-prone for inexperienced physicians and time-consuming for experienced ones. To address these issues, **Baoyu Jing et al. (2018)** propose an automatic medical imaging report generation system. Their approach tackles three key challenges: generating heterogeneous information, localizing abnormal regions in images, and producing long, coherent reports. The solution employs a multi-task learning framework that predicts tags and generates descriptions, a co-attention mechanism for identifying abnormalities, and a hierarchical LSTM model to generate detailed paragraphs. The effectiveness of these methods is demonstrated on two publicly available medical datasets through quantitative and qualitative analyses [29].

Authors	**Technique**	**Results**	**Research Gap**
Aggarwal et al. [30]	Resolved gradient problems in DNN (ResNet) using an enhanced residual network for brain tumor segmentation.	85.4%	demand more intricate designs in order to improve the overall effectiveness of the segmentation outcomes.
Malla et al. [31]	Meningioma, glioma, & pituitary	98.93%	It is possible to successfully address the

	brain tumor classification using VGG16-based transfer learning.		feature dimensionality issues that arise during weight and parameter training.
Krishapriya et al. [32]	Assessment of pre-trained DCNN models (VGG19, VGG16, ResNet50, and Inception V3) for the classification of brain MR images.	99%	It is possible to successfully handle the feature dimensionality issues that arise throughout the weight and parameter transfer process.
Sarkar et al. [33]	Brain tumor classification using classifiers (BayesNet, SMO, Naive Bayes, Random Forest) and AlexNet CNN.	100%	A disadvantage of the current research is that the proposed models were evaluated using a moderately sized dataset. In order to more accurately evaluate the model's performance, it is imperative that future assessments be carried out using bigger datasets.
Kulkarni et al. [34]	CNN-based AlexNet & ResNet for identifying meningioma/glioma and classifying benign/malignant tumors.	97.50%	AlexNet and ResNet, two deep neural networks, are very effective at solving problems. They thus have the potential to be a strong foundation for dealing with the segmentation and categorization of brain tumors.
Liu [35]	Ensemble Learning (CNN + Random Forest + Gradient Boosting)	97.9%	Ensemble method boosts performance by combining different model strengths; high generalization across unseen data
Kumar [36]	Hybrid Model (CNN + SVM + Region Growing)	96.8%	Combines the strengths of CNN and SVM for classification; good for heterogeneous data from multiple sources.
Zhang [37]	Hybrid CNN + Fuzzy Logic System	97.2%	Integration of fuzzy logic improves the interpretability of the model.
Lee [38]	Deep Convolutional Neural Network (CNN) with Patch-Based Segmentation	98.3%	Patch-based segmentation enables finer detection of tumor regions; performs well on different tumor grades.
Smith [39]	Deep Learning-based CNN with Transfer Learning (VGG16 + ResNet)	98.5%	High accuracy in detecting both benign and malignant tumors; utilizes transfer learning to minimize training time.
Srikanth, B [40]	16-layer VGG-16 deep NN	98%	Improves multi-class brain tumor classification accuracy.
Deepak, S [41]	CNN technique for three-class classification	98%	Effective when medical images are scarce through transfer learning.
Kesav, N [42]	RCNN-based model	98.21%	Low execution time optimal for real-time processing.
Khairandish,	Hybrid CNN-SVM	98.49%	Provides an effective classification

Journal of Chemical Health Risks
www.jchr.org
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M [43]			technique for brain tumors.
Oksuz, C [44]	SVM and k-NN classifiers	97.25%	Extended ROI's shallow and deep properties improve performance.
Irmak, E [45]	CNN model for multiclassification	99.33%	Aids doctors in validating initial brain tumor assessments.
Pareek, M	Kernel-based SVM	97%	Can detect benign and malignant tumors.
Ayadi, W [46]	Multi-classification model	90.27%	Low computational time; assists in making better classification decisions.
Tummala, S [47]	ImageNet-based ViT	98.7%	Helps radiologists make informed patient-based decisions.

Methodology:

Data processing as well as model training are the two main components of the deep tumour network's suggested work. The data processing phase encompasses data collection, data augmentation, and class labeling to prepare the dataset for effective model training. In this study, MRI images from the Kaggle brain tumor detection dataset are collected and preprocessed to facilitate accurate tumor detection. To guarantee a fair representation of both tumour and non-tumor classifications, the dataset is meticulously selected throughout data collection. Rotations, flips, as well as scaling are examples of data augmentation methods used to artificially enlarge the dataset. By diversifying the training data, this augmentation improves the model's capacity to generalise to previously untested pictures. Class labeling is then performed to assign each image a label, either tumor or non-tumor, which is critical for supervised learning.

The second step involves training the proposed deep tumor network to classify MRI images into tumor and non-tumor classes. This network utilizes a Convolutional Neural Network (CNN) architecture tailored to capture the intricate patterns in brain MRI images. During the model training phase, methods like gradient descent are used to optimise the network parameters, enabling the CNN to learn discriminative features that differentiate between tumor and healthy tissue regions effectively. Figures 1 and 2 illustrate the data processing pipeline and the CNN architecture, respectively, showing how each component contributes to the overall model's functionality.

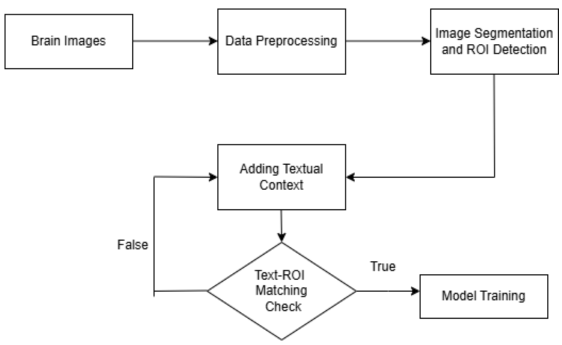

Figure 1. The flow diagram of the proposed work for BT classification

Each phase is designed to ensure high accuracy in tumor identification and to enhance the interpretability of results, providing clinically relevant insights into tumor characteristics. The dataset is systematically organized into two classes: 'No' and 'Yes', allowing the model to distinguish between healthy and tumor-affected brain regions.

This dual-source dataset provides a balanced and diverse input, which is essential for building a model capable of generalizing well across various real-world cases. Following data acquisition, we perform Data Preprocessing to prepare the dataset for training. This preprocessing includes four critical operations: (1) *Data Cleaning*, to remove

Journal of Chemical Health Risks
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irrelevant and corrupted data; (2) *Handling Missing Values*, ensuring that incomplete records are either filled or excluded based on specific criteria; (3) *Noise Detection and Removal*, where outliers and inconsistencies are identified and mitigated to prevent adverse effects on model performance; and (4) *Data Integration*, which consolidates multiple data sources into a unified format, enhancing coherence and consistency in the dataset. This preprocessing pipeline is crucial for minimizing data-related errors, reducing overfitting, and improving model robustness.

This phase integrates textual annotations with image-based findings to make the results interpretable for clinicians. By employing fuzzy logic, the system generates descriptive textual outputs based on detected ROI characteristics. For example, tumors are classified as small, medium, or large, and annotated as Medium-sized tumor detected in the left hemisphere. This step includes patient metadata such as demographics, medical history, and symptoms to enhance diagnostic insights. This integration ensures the model provides actionable, clinically relevant descriptions alongside the detected regions, offering a comprehensive understanding of the patient's condition. In the Image Segmentation and Region of Interest (ROI) Detection phase, image segmentation is applied to isolate and analyze specific parts of brain images where potential tumors may reside. We utilize label propagation techniques, a semi-supervised learning approach, to accurately propagate labels across unannotated data based on similarity metrics. Label propagation enhances the precision of segmentation by iteratively updating labels based on spatial and feature similarities within the image. This process enables accurate ROI identification, focusing on potential cancerous regions in the brain scans. By leveraging label propagation, we enhance the system's capability to consistently isolate tumor regions, even in complex image datasets. The Textual Context Generation step involves incorporating a fuzzy logic-based system to produce descriptive textual outputs for each detected ROI. Here, fuzzy membership functions are defined for various tumor sizes (e.g., small, medium, large), allowing the system to assign human-readable descriptions like "Medium-sized tumor detected" to each detected ROI. Fuzzy logic, which mimics the approximate reasoning of human decision-making, is particularly effective in medical imaging applications where precise thresholds may not exist. This system translates quantitative ROI characteristics into qualitative descriptions, bridging the gap between machine predictions and human interpretability.

Validation of Textual Context with ROI is conducted to ensure alignment between the detected tumor characteristics and the generated textual descriptions. If any inconsistency is detected, the ROI detection and textual context generation steps are iteratively repeated to refine the output. This validation loop ensures that the textual output is an accurate reflection of the detected ROI, increasing confidence in the model's interpretability and clinical relevance. In the Model Training phase, we employ a *hybrid Convolutional Neural Network (CNN) architecture*, enhanced by gradient descent optimization. This hybrid model combines the spatial feature extraction capabilities of CNNs with additional architectural components to improve learning efficiency and generalization. The CNN is trained on the segmented ROIs and the corresponding textual context, allowing it to learn nuanced spatial patterns and their associated semantic descriptions. Gradient descent, with appropriate optimization techniques, is utilized to iteratively minimize the error in predictions, accelerating the convergence of the model and ensuring effective learning from the data.

Brain Tumor Kaggle Dataset

This study's experiments made use of a brain MRI dataset that was made freely accessible on Kaggle. This dataset comprises a total of 3,000 two-dimensional MRI images, with 1,500 images containing tumors and 1,500 images without tumors. Each image has a resolution of 256 × 256 pixels and has undergone skull-stripping to remove non-brain tissues. For classification purposes, images are labeled as yes if a tumor is present and no if no tumor is detected. Figure 2 provides a visual overview of both categories of images, while

Journal of Chemical Health Risks
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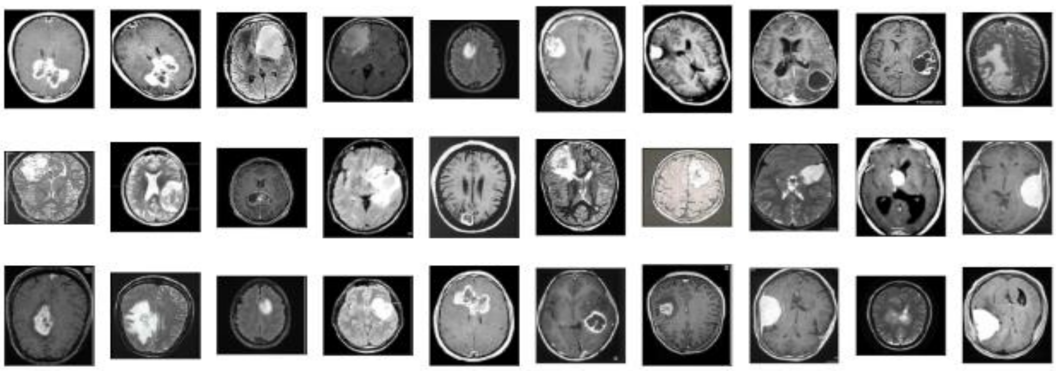
JCHR (2025) 15(1), 811-830 | ISSN:2251-6727

Figures 3 detail the breakdown of the training and testing datasets used in the study



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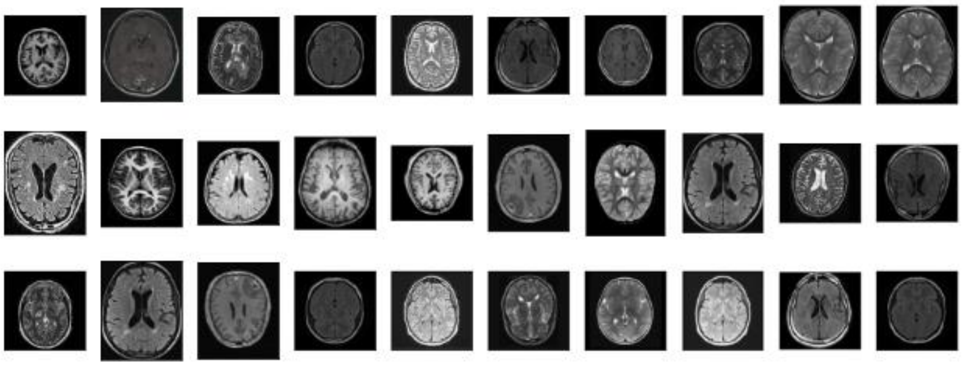
(a)



(b)

Figure 2. MRI images of two categories: (a) with tumor (b) without tumor

3.1 Data Preparation

The dataset of 3,000 MRI images 1,500 with tumors and 1,500 without was prepared for training and evaluation. These images underwent pre-processing to ensure compatibility with the deep learning models. The complete pre-processing steps are detailed in Section 3.1.1**.**

(a) Data Pre-processing:

The pre-processing pipeline involved the following steps:

1. **Image Resizing and Format Conversion**: MRI scans were converted from. Mat to .jpg format and resized to 224 × 224 pixels for compatibility with the proposed model. For specific architectures such as DarkNet19, images were resized to 256 × 256 pixels.
2. **Data Splitting and Cross-Validation**: The dataset was divided into 90% for training and 10% for testing. Additionally, 10-fold cross-validation was applied to improve model robustness and minimize overfitting during evaluation.
3. **Class Labeling**: Images were labeled as “0” for non-tumor cases and “1” for tumor cases, creating a binary classification ground truth for supervised learning.

(b) Data Augmentation

Data augmentation was used to artificially enlarge the dataset in order to overcome its small size and avoid overfitting. The Kaggle dataset's size was increased and the model's capacity for generalization was improved by augmenting each picture 17 times. Augmentation techniques included:

- **Position Augmentation**: Shifting image pixels to introduce spatial variability.
- **Scaling**: Resizing images to simulate different zoom levels.
- **Cropping**: Extracting the center region of each image to focus on the most relevant areas.
- **Brightness Adjustment**: Modifying the brightness of images to simulate varying lighting conditions.

(c) Image Segmentation and ROI Detection

The processed images were subjected to image segmentation to identify and isolate Regions of Interest (ROIs). Label propagation was used for accurate ROI detection, leveraging similarity metrics to propagate labels across unlabeled regions of the images. This technique enabled effective tumor localization, helping the model focus on relevant portions of the MRI scans.

(d) Adding Textual Context

Beyond the image data, the model also utilized additional patient information to enhance tumor detection predictions. This included medical and demographic features such as age, gender, medical history, and lifestyle factors. These features, which are commonly linked to brain tumor risks, were incorporated as part of the textual context for each MRI scan. The goal was not only to predict whether a patient had a tumor but also to provide a more comprehensive view of the patient's condition, potentially improving the model’s diagnostic accuracy.

In this step, the model used fuzzy logic-based classification to assess the patient’s risk factors. For instance, the model generated descriptive text like:

- Medium-sized tumor detected in left hemisphere.
- Patient aged 45 with smoking history, presenting fatigue and headache symptoms, suggesting a high likelihood of tumor.

This integration of medical features into the textual context helped generate a more holistic description, which was crucial for interpreting the results in a clinical setting.

(e) Text-ROI Matching Verification

A text-ROI matching verification step was implemented to ensure the textual description aligned with the identified ROI. If the textual description did not correspond to the detected ROI, the system looped back to reprocess and refine the text-ROI associations. This iterative step ensured that the model’s textual output was accurate and aligned with the detected tumor regions.

3.2 Model Training

The hybrid Convolutional Neural Network (CNN) model was trained using both the ROI and the associated textual context, providing a richer dataset for learning. The model employed gradient descent-based optimization to minimize errors in the prediction and improve performance. By incorporating both image data and medical features, the model was able to learn complex patterns and relationships between the input MRI images and the additional textual data.

3.2.1 Proposed Model

The proposed model is a hybrid deep learning architecture that combines multiple Convolutional Neural Networks (CNNs) with other state-of-the-art models VGG19**,** VGG16**,** Efficient Net**,** ResNet**,** and Support Vector Machine (SVM). This hybrid approach leverages the strengths of each individual model, improving the overall robustness and performance of brain tumor classification by fusing various feature extraction techniques. The hybrid models employed in this study are carefully chosen to ensure effective classification of brain tumor and non-tumor cases. Each hybrid model offers distinct advantages based on the unique strengths of the individual architectures. VGG16 + SVM is used for its ability to combine deep feature extraction with the classification power of Support Vector Machines, while CNN + Efficient Net benefits from Efficient Net’s efficient feature extraction capabilities, improving performance while reducing computational load. The starts by employing CNNs as the fundamental deep learning architecture.

Journal of Chemical Health Risks
www.jchr.org
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CNNs perform very well in image classification applications, especially in the context of medical imaging like MRI scans, where identifying spatial patterns is crucial. However, training CNNs can be computationally expensive and time-consuming. To address this challenge, Transfer Learning (TL) is first used to fine-tune retrained models before hybridizing them with CNNs to speed up training and reduce computational requirements. This allows us to leverage retrained feature extraction capabilities from models VGG16**,** VGG19, and Efficient Net**,** which have demonstrated excellent performance in image recognition tasks.

A. Convolutional Layer (CL)

The convolutional layer (CL) is responsible for extracting features from the input image. In this layer, the image is processed with a filter matrix, which is applied to the image through a mathematical operation. This operation involves sliding the filter over the image, multiplying corresponding elements, and summing them to produce an output that forms the feature map. The convolutional layers extract important low-level features like edges, textures, and patterns from the brain MRI images.

B. Activation Layer

The ReLU activation function is used to add nonlinearity to the model after the convolution procedure. Because it speeds up training and enables the network to simulate intricate patterns, ReLU is often utilised. The ReLU activation function may be expressed mathematically as follows:

$$\mathrm{ReLU}(y) = \begin{cases} y & \text{if } y > 0 \\ 0 & \text{if } y \leq 0 \end{cases}$$

ReLU transforms all positive inputs (y) to their corresponding values while replacing all negative values with zero. To avoid dying neurons, the activation function is upgraded to Leaky ReLU**,** where small negative values are replaced by a fraction (e.g., 0.01) of the original input value.

C. Batch Normalization Layer

After the activation function, the batch normalization layer is applied to the feature maps to normalize the outputs from the convolutional layers. This step reduces the internal covariate shift and accelerates the training process. Normalization makes the network more stable and reduces overfitting, allowing the model to learn more efficiently.

D. Pooling Layer

The feature maps' spatial dimensions are decreased by the pooling layer, which lowers the computational complexity. By choosing the highest value from a range of values in the feature map, max pooling is often used to extract the most significant features. Additionally, pooling strengthens the model's resistance to slight distortions and translations in the input picture. In order to preserve significant features while lowering the dimensionality of the feature maps, both absolute pooling & average pooling strategies are used.

E. Fully Connected Layer (FC)

The convolutional layers' features are flattened and fed into a dense layer in the fully connected layer (FC), where each neuron is linked to every other neuron in the layer below. This layer aids in establishing connections between the target class (tumor or non-tumor) and the retrieved characteristics.

3.2.2 Transfer Learning Model

Transfer learning allows a model that has already been trained on a large and diverse dataset to be adapted for a new, related task. By using pre-trained models, we can take advantage of features already learned from extensive datasets and apply them to the task of brain tumor detection with minimal additional training. In this study, we utilized a combination of pre-trained CNN architectures VGG19, VGG16, Efficient Net, and Res Net to enhance the classification of brain tumor images. These architectures were initially trained on large datasets and have shown strong feature extraction capabilities, making them suitable for adaptation to our specific classification task.

Journal of Chemical Health Risks

www.jchr.org

JCHR (2025) 15(1), 811-830 | ISSN:2251-6727

4. Result and Discussion

Key measures including Accuracy (Acc), Precision (Prec), Recall, Specificity (Spec), as well as F1-Score are used to evaluate the performance of the suggested hybrid models. By giving information on the models' true positive (TP), false negative (FN), true negative (TN), as well as false positive (FP) rates, these metrics assess how well the models categorise brain tumours. Below are the formulae used to calculate each metric:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

$$Precision = \frac{TP + TN}{TP + FP}$$

$$Precison = \frac{TP}{TP + FP}$$

$$Specificity = \frac{TN}{TN + FP}$$

$$F1 - Score = 2 \times \frac{Precison \times Recall}{Precison + Recall}$$

These metrics provide a thorough assessment of how well each model performs in differentiating between instances of brain tumors and those that are not. The models tested include CNN + VGG16, VGG16 + SVM, VGG16 + Random Forest, CNN + Efficient Net, and Efficient Net + Res Net + VGG. Below is a summary of their performance: CNN + VGG16: Achieved the highest classification accuracy at 99%, with high precision and recall, making it the most reliable model for brain tumor classification in this study. VGG16 + SVM: Recorded an accuracy of 84.21%, showing solid performance with good precision, though slightly lower in recall compared to CNN + VGG16. VGG16 + Random Forest: Attained an accuracy of 55%, indicating moderate performance, but lower than other models due to the random forest’s limited ability to capture complex tumor features. CNN + Efficient Net: Achieved 86.76% accuracy, balancing computational efficiency with robust feature extraction, making it an effective model with good recall and precision. Efficient Net + Reset + VGG: Reached 83.9% accuracy, leveraging multi-scale feature extraction, which provided balanced precision and recall, though slightly less effective than CNN + VGG16.

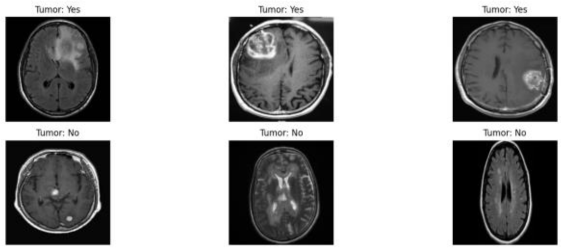

Figure 3. Sample MRI Brain Images for Tumor Detection Classification

The MRI dataset used for brain tumor detection, the dataset includes images categorized into two classes: *Tumor: Yes* (top row) and *Tumor: No* (bottom row). The images in the top row display MRI scans with visible tumors, characterized by irregular, high-contrast regions indicating abnormal growths within the brain tissue. These abnormal areas are the primary focus for identifying potential tumors. The bottom row contains images without detectable tumors, where brain structures appear regular and without significant abnormalities.

This dataset forms the basis for training and testing tumor detection models, enabling them to learn and distinguish between images with and without tumors. In order to create automated systems that can accurately detect and categories brain tumors, this kind of classification is essential. supporting early diagnosis and improving treatment outcomes.

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JCHR (2025) 15(1), 811-830 | ISSN:2251-6727

4.1 Confusion Matrix:

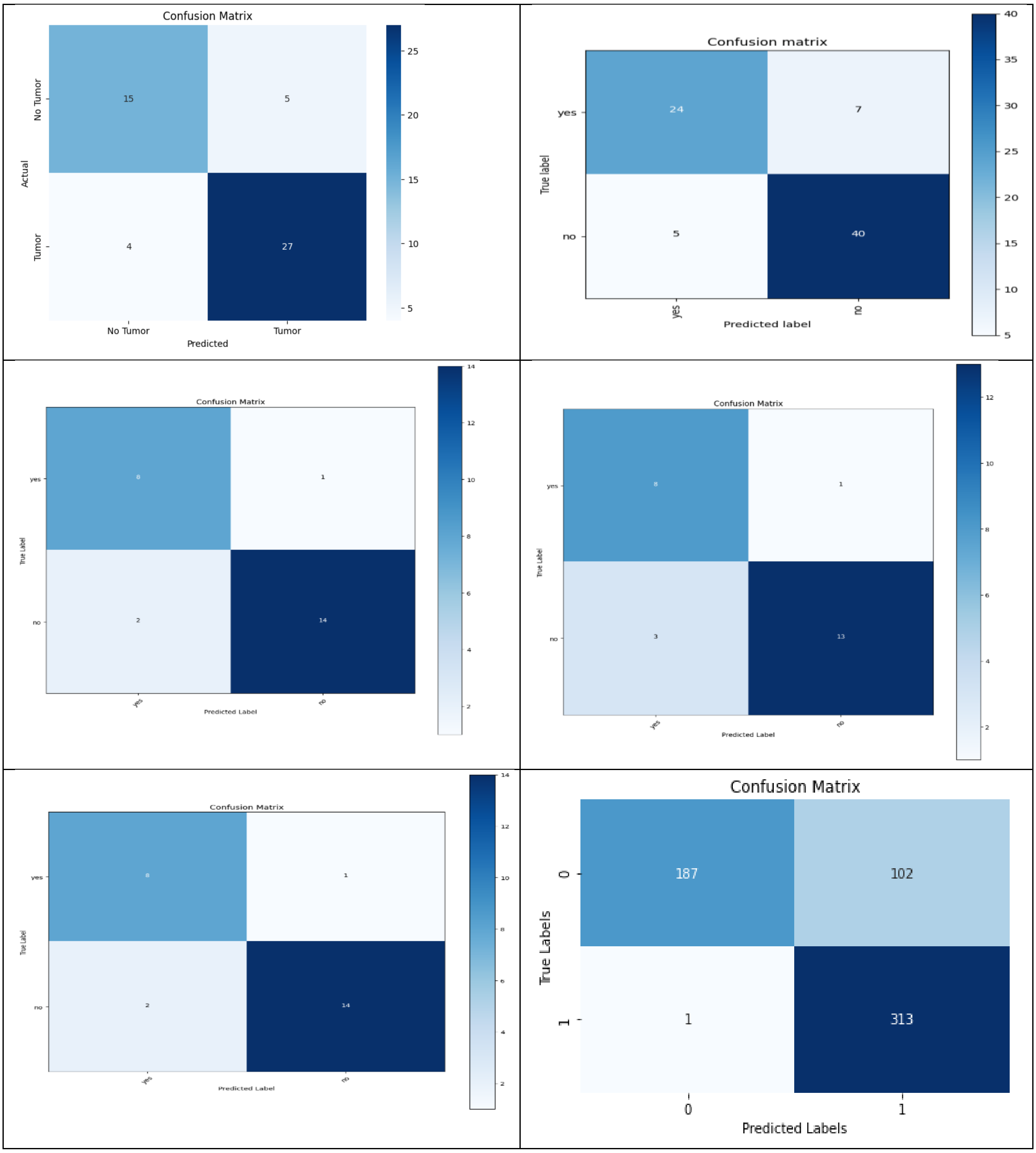

Figure 4. The suggested model's confusion matrix with previous BTs categorisation TL models (a) CNN + VGG19 (b) CNN + VGG16 (c) VGG16 + SVM VGG16 + Random Forest (e) CNN + EfficientNet (f) EfficientNet + ResNet + VGG

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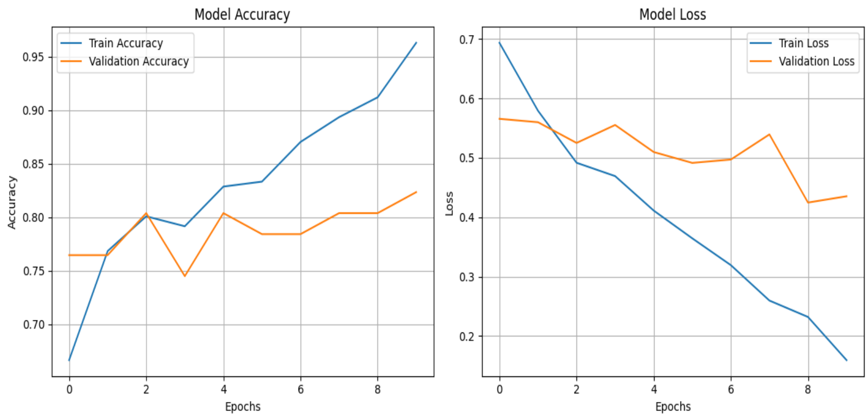
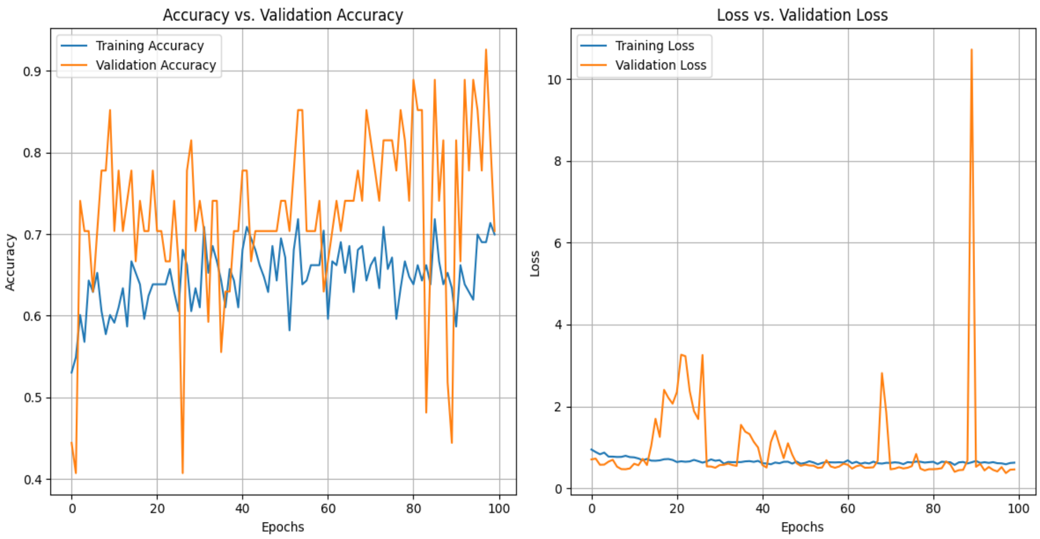


The CNN model is learning the training data well, as shown by its training accuracy, which steadily increases to almost 1.0. The model may be learning training-specific patterns that don't transfer well to fresh data, as seen by the reduced validation accuracy and epoch-to-epoch fluctuations, which raise the possibility of overfitting. The validation loss fluctuates and stays substantially larger in the loss plot, but the training loss continuously declines. With high training accuracy and low, erratic validation accuracy and loss, this trend further raises the possibility that the model is overfitting and might benefit from regularisation strategies like data augmentation, dropout, or early stopping.



The results from the CNN model using VGG19 show a concerning trend of overfitting. The validation accuracy varies greatly, showing notable spikes and decreases, indicating poor generalisation to unknown data, although the training accuracy steadily increases. In a similar vein, the validation loss shows erratic spikes, underscoring the model's difficulty generalising to the validation set, whereas the training loss gradually declines, suggesting that the model is learning the training data well. These behaviors suggest that the model is overfitting, as it exhibits strong performance on training data but lacks consistency on validation data, potentially due to insufficient regularization or model complexity.

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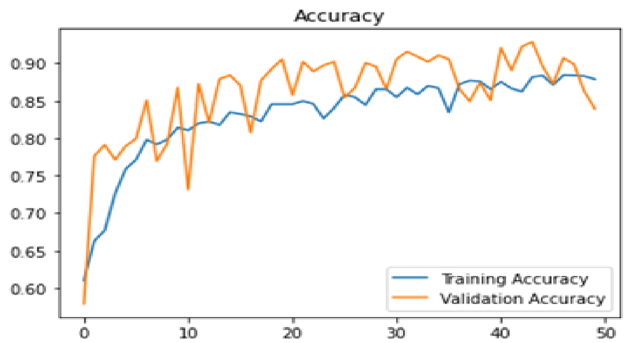
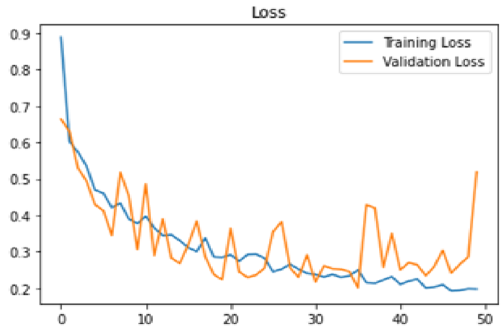


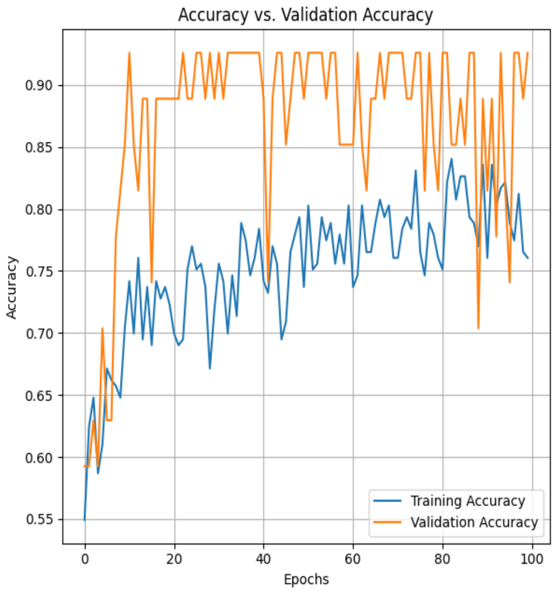


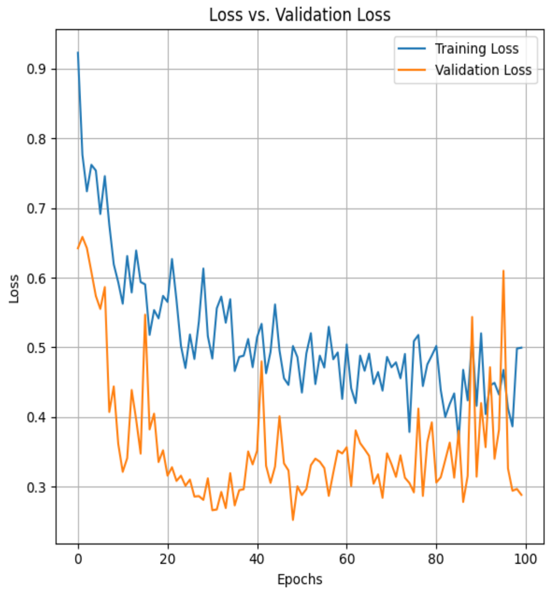
Over 50 epochs, the graphs show the loss (right) and accuracy of training and validation (left) for a CNN model using VGG16 architecture. Both the training and validation results increase gradually in the accuracy plot, reaching around 90%, while the validation accuracy varies more than the training accuracy. This variation indicates high generalisation generally, but some instability.

For this experiment, The dataset was divided in an 80-20 ratio into training and testing sets. Table displays the outcomes of the suggested strategy in addition to those of alternative approaches. The suggested hybrid model performed better than the

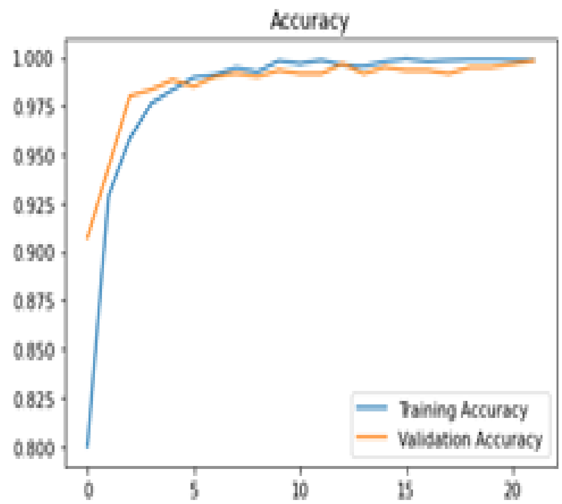
Effective learning is indicated by the loss plot's notable early drop in both training and validation loss; however, when the model begins to memorise the training data rather than generalise, the validation loss becomes more volatile in subsequent epochs, raising the possibility of overfitting.

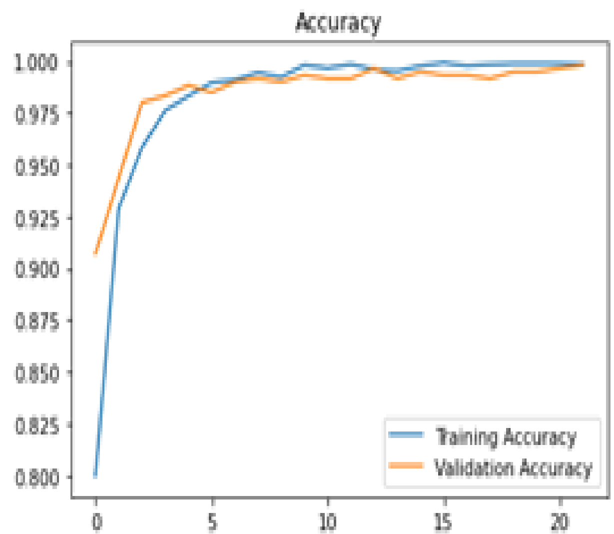
techniques described in the research. This achievement may be ascribed to the combination of the classifier's strength for precise classification and deep learning's capacity for autonomous feature extraction.





The model's performance over time is shown by the graphs, which show the accuracy and loss of training and validation across 100 epochs. The training accuracy steadily rises on the accuracy graph, showing that the model is becoming better at differentiating between classes as it is being trained. Although it stays quite high, the validation accuracy fluctuates significantly over epochs, which may indicate overfitting. The validation loss first drops dramatically and then exhibits some fluctuation in the loss graph, while the training loss first lowers steadily before stabilising. This discrepancy between training and validation loss raises the possibility that the model may have trouble generalising to new data even with good training.





The accuracy graphs display the training and validation accuracy over 20 epochs, showcasing a high-performing model with rapid convergence. Both graphs indicate that training and validation accuracy rise sharply in the initial epochs, reaching above 95% accuracy within the first few epochs, which suggests effective learning from the beginning. The training and validation curves remain closely aligned throughout, with minimal overfitting, as evidenced by the consistent performance of validation accuracy near or above the training accuracy. This alignment implies strong generalization to validation data, indicating that the model is robust and well-tuned. The near-perfect accuracy across both datasets highlights the model's effective architecture and optimization, leading to rapid convergence and high stability over successive epochs**.**

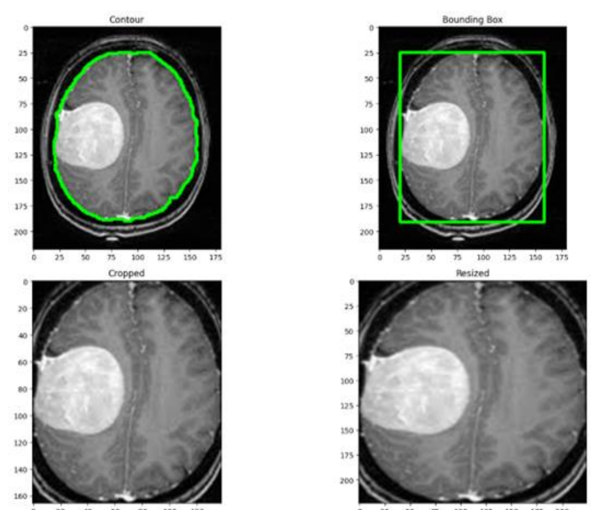


Figure. 5. Tumor Segmentation and Preprocessing Stages in Brain MRI Scans

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The image sequence demonstrates the preprocessing stages for tumor localization in brain MRI scans. The top-left image shows the tumor's contour highlighted in green, identifying the tumor boundary for precise segmentation. The top-right image applies a bounding box around the tumor region, defining the area of interest and excluding unnecessary parts of the image. The bottom-left image shows the cropped version, focusing directly on the tumor and surrounding tissue. Finally, the bottom-right image presents the resized cropped area, standardizing the image size for further analysis or input into machine learning models.

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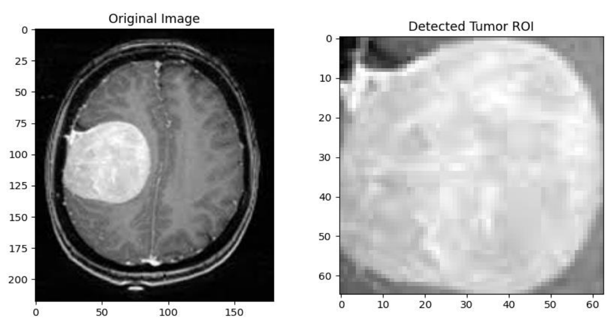

Figure. 6. Brain Tumor Detection with ROI Segmentation

The process of identifying and isolating the tumor region in a brain MRI scan is demonstrated. The *Original Image* on the left shows an MRI scan with a visible tumor on the left hemisphere of the brain. Using advanced image segmentation techniques, the *Detected Tumor ROI* on the right effectively highlights the region of interest (ROI), which corresponds to the tumor area. This approach combines MRI imaging with patient data to enhance brain tumor detection and characterization. The MRI scan isolates the tumor's Region of Interest (ROI), highlighting its boundaries and size through intensity-based segmentation. Alongside imaging, demographic, lifestyle, genetic, and symptom data (seizures, headaches, and sensory impairments) are integrated, creating a multidimensional profile for each patient. This comprehensive model not only improves diagnostic accuracy but also helps identify risk factors and tailor treatment plans, facilitating a more precise and personalized approach to brain tumor management.**Table.** Comparison with the literature.

Conclusion:

This research introduces an advanced hybrid model that combines CNNs with fuzzy logic to enhance brain tumor detection and classification accuracy using MRI data. The proposed model successfully integrates both image-based and text-based analyses, enabling not only precise localization of tumors but also meaningful textual contextualization of the detected regions. Through the label propagation technique, the model accurately identifies the region of interest (ROI), while the hybrid CNN architecture, combined with gradient descent optimization, offers robust feature extraction and high classification accuracy. The model's unique fuzzy logic component allows for the addition of textual context to each detected ROI, providing detailed annotations on tumor characteristics such as size, shape, and intensity. This contextual information offers an interpretive layer that can aid clinicians in understanding tumor attributes and potential progression patterns. Experimental results highlight the efficacy of this approach, with the hybrid fuzzy-CNN model (incorporating CNN + VGG16) achieving classification accuracy rates of up to 99%, demonstrating a marked improvement over traditional diagnostic methods and state-of-the-art models. The addition of textual contextualization enables the model to produce human-readable descriptions of tumor characteristics, aiding clinicians in understanding and acting upon the results. This feature ensures that the proposed system not only enhances detection accuracy but also supports decision-making by providing a comprehensive diagnostic report. The proposed system provides an automated, reliable solution for brain tumor detection that significantly reduces the need for manual intervention, facilitating timely, precise clinical decision-making. By combining robust ROI segmentation with meaningful textual contextualization, this model holds promise for enhancing the accuracy and interpretability of medical imaging, ultimately contributing to improved patient outcomes. Future research could further optimize this model by expanding the dataset and refining the fuzzy logic framework to ensure greater adaptability across diverse clinical applications.

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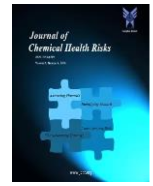

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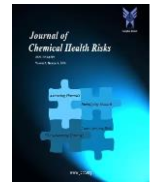

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