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

A DEEP LEARNING BASED BRAIN TUMOR DETECTION AND LOCALIZATION

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Abstract - Accurate brain tumor detection and localization are essential for timely diagnosis and treatment in medical imaging. In this paper, we propose an advanced deep learning model using Convolutional Neural Networks (CNN) integrated with ResNet-101 for brain tumor detection, tumor localization, and classification of missing modality images. The model leverages the residual learning capabilities of ResNet-101 for effective feature extraction, enhancing the detection of brain tumors even in incomplete or missing modality. Additionally, a localization module is incorporated to pinpoint the tumor region, improving interpretability for clinical use. Results demonstrate that the CNN-ResNet-101 model excels in tumor detection and classification, maintaining high accuracy across both complete and missing modality images. Furthermore, the model's ability to localize tumors without compromising classification performance is highlighted through improved precision and recall scores. The proposed model achieves better performance for robust brain tumor detection and localization in challenging medical imaging conditions. The proposed model is evaluated and benchmarked against other techniques, with a comprehensive performance comparison using key metrics such as accuracy, precision, recall, and F1-score.

Keywords: Brain Tumor Detection, Missing Modality, Segmentation, Localization, Convolutional Neural Networks, ResNet

I. INTRODUCTION

Accurate detection and localization of brain tumors are crucial for the timely diagnosis and treatment of patients in medical imaging. Due to the complexity of brain tumors and the variability in imaging modalities, advanced computational techniques are required to assist radiologists and healthcare professionals in identifying and analyzing abnormalities efficiently. Over time, the integration of artificial intelligence (AI) and machine learning (ML) has significantly improved diagnostic processes in medical imaging. Among these innovations, deep learning models, especially those utilizing Convolutional Neural Networks (CNNs), have become essential tools for image analysis. This paper presents a novel method that incorporates the power of CNNs combined with ResNet-101 to improve brain tumor detection, localization, and classification of images with missing modalities [1]. Brain tumors pose a considerable challenge in medical imaging due to their heterogeneous nature, irregular shapes, and unpredictable growth patterns. Traditional diagnostic methods often rely on the manual interpretation of experienced radiologists, which is time-consuming and susceptible to human error. Furthermore, missing or incomplete imaging data exacerbates the diagnostic process, as these gaps hinder accurate tumor detection and classification. To address these issues, the proposed model leverages the strengths of residual learning through ResNet-101, a deep neural network known for its exceptional feature extraction capabilities. By tackling the challenges of incomplete imaging data, the model ensures reliable tumor detection and localization, even when imaging conditions are suboptimal.

The foundation of the proposed method is the integration of ResNet-101 within the CNN framework. ResNet-101 employs residual connections that alleviate the vanishing gradient problem, a common obstacle when training deep networks. These connections enable the network to learn hierarchical features more efficiently, capturing subtle patterns and textures critical for distinguishing tumors from healthy brain tissue. This advanced feature extraction ability ensures that the model excels at identifying abnormalities with high precision, even in the presence of complex or noisy data. By utilizing the residual learning architecture, the model achieves superior performance in cases where traditional CNN models may struggle. In addition to its robust feature extraction, the proposed model features a localization module that accurately identifies the precise location of brain tumors within an image. This module enhances the model's interpretability, providing clinicians with visual cues to better understand the tumor's spatial distribution. Localization is especially vital in medical imaging, as it offers insights that can inform surgical planning, radiotherapy, and other treatment approaches. The localization module uses advanced techniques to accurately delineate tumor regions, ensuring critical areas are highlighted while maintaining the model's overall classification accuracy.

2. LITERATURE REVIEW

Brain tumor detection is critical in medical imaging, and machine learning techniques, particularly deep convolutional neural networks (CNNs) like VGG-16, have demonstrated great potential in enhancing accuracy and efficiency. VGG-16, a deep CNN architecture pre-trained on large image datasets, can be fine-tuned via transfer learning on smaller brain tumor datasets to identify relevant features. Sasupalli Rohith et al leverages VGG-16 for brain tumor detection by pre-processing images to enhance contrast and remove noise, extracting features with VGG-16, and using these features to train an SVM classifier to distinguish between tumor and non-tumor images. The method achieves over 95% accuracy, showcasing its promise in improving diagnostic processes. However, limitations include the reliance on pre-trained models, which may not fully capture domain-specific features, the need for substantial computational resources, and potential performance variation with different datasets or pre-processing methods [2][3]

MRI (Magnetic Resonance Imaging) is a critical tool for detecting brain tumors, typically followed by biopsy or surgical tissue analysis to determine tumor type. However, this manual process is time-intensive and prone to misdiagnosis if the specialist lacks sufficient experience. In this research Hanming Hu et al explores the application of deep learning models, including VGG16/19, AlexNet, GoogleNet, ResNet, and YOLO, to enhance brain tumor detection and diagnosis using MRI images. YOLO was specifically implemented to localize tumors in MRI scans and improve classification through graphical enhancements, though these steps led to decreased classification accuracy. The results indicate that deep learning models can significantly improve the speed and accuracy of brain tumor diagnosis. However, limitations in life span calculation, such as predicting tumor progression or survival time, remain unaddressed, as current models primarily focus on detection and classification rather than prognostic evaluation. Further research is needed to integrate life span prediction into deep learning-based diagnostic systems [4][5].

Brain tumors are cancerous growths in the brain where early diagnosis is critical for effective treatment. Magnetic resonance imaging (MRI) is commonly used for diagnosis, and deep learning techniques such as Convolutional Neural Networks (CNNs) are well-suited for classifying large image datasets. Support Vector Machine (SVM) is another machine learning approach widely used for classification tasks. In this research Kavya Duvvuri et al classified brain MRI images using pre-trained models like AlexNet, VGG16, InceptionV3, and ResNet50. Additionally, a hybrid CNN-SVM model was developed by training CNN and SVM on the same dataset to improve accuracy and predictions. While the hybrid approach enhanced classification performance, a key limitation is tumor localization. The models focus primarily on classification rather than accurately identifying the tumor's exact location within MRI scans, which is essential for clinical decision-making and treatment planning. Future work should address integrating robust localization mechanisms into the diagnostic framework.[6][7].

A tumor is the abnormal growth of cells in the human body, with brain tumors being particularly severe due to their potential to cause central nervous system issues, mental disabilities, muscle paralysis, and even fatal outcomes. Early detection is critical to mitigate these effects, but traditional tumor detection using MRI (Magnetic Resonance Imaging) is a time-consuming, human-driven process prone to errors. To address this, B Shashank Sai et al proposed an autonomous tumor detection model using convolutional neural networks (CNNs) for identifying Gliomas. Robust networks like VGG16 and VGG19 are employed, achieving high accuracy rates of 95% and 96%, respectively. The model enhances feature extraction through a deconvolution process on VGG16, followed by CRF-RNN in the final layer for classification, yielding a classification accuracy of 92.3%. However, a notable limitation is the model's performance on missing modality images, where certain imaging sequences may be unavailable. This affects the classification accuracy and reliability, as the model struggles to compensate for the absent data. Future research should focus on developing techniques to handle missing modalities effectively, ensuring consistent and accurate tumor classification [8][9].

3. PROPOSED SYSTEM

3.1 Problem Statement

Existing systems for brain tumor detection and localization primarily rely on manual analysis by radiologists, which is time-consuming, error-prone, and often lacks consistency. Automated systems utilizing Convolutional Neural Networks (CNNs), such as the VGG16 architecture, have been introduced to address these limitations. These systems typically involve preprocessing brain MRI images, extracting hierarchical features through VGG16's convolutional and pooling layers, and classifying the presence of a tumor. However, while VGG16 presents a promising solution, it suffers from overfitting, high computational costs, and limited robustness to missing or incomplete imaging data. Additionally, current methods face several critical limitations, including potential inaccuracy in detecting subtle abnormalities, lack of robustness to variations in image quality and noise, and insufficient interpretability for pinpointing the exact tumor location, which can hinder clinical decision-making and necessitate further manual intervention. These challenges highlight the need for more accurate, robust, and interpretable systems for effective brain tumor detection and localization.

3.2 ResNet Model

The implementation of the proposed brain tumor detection and localization framework using CNN ResNet-101 involves several key steps, leveraging its advanced architecture to handle both complete and missing modality images effectively. Below, we outline the methodology in detail:

1. **Dataset Preparation**: The framework begins with the collection and preprocessing of a comprehensive brain imaging dataset. The dataset includes MRI scans with annotations for tumor regions, encompassing both complete and missing modality images. Preprocessing involves normalization, resizing of images to a uniform dimension, and data augmentation techniques such as rotation, flipping, and cropping to increase the diversity of training samples.
2. **Model Architecture**: The core of the framework is the integration of ResNet-101 into the CNN architecture. ResNet-101, with its 101-layer deep residual network, is utilized for robust feature extraction. The residual connections address vanishing gradient issues and enable the learning of hierarchical features essential for tumor detection. The architecture is further enhanced by incorporating a localization module, which uses feature maps to predict the spatial distribution of tumors within the brain images.
3. **Handling Missing Modalities**: To address missing modality scenarios, the model employs a hybrid strategy that uses residual learning to compensate for incomplete data. Feature extraction layers are optimized to identify critical patterns even in the absence of certain imaging modalities. Data imputation techniques are also explored to reconstruct missing modalities during training, ensuring the model generalizes effectively across diverse inputs.
4. **Evaluation Metrics**: The performance of the framework is evaluated using metrics like accuracy, precision, recall, F1-score. These metrics provide a comprehensive understanding of the model's ability to detect and localize tumors effectively. Additionally, visualizations of localization outputs are analyzed to validate the model's interpretability.

Through this structured methodology, the CNN ResNet-101 framework is positioned as a robust solution for brain tumor detection and localization, addressing the challenges of incomplete imaging data while maintaining high precision and interpretability.

3.3 Mathematical Equation

The mathematical formulation of the brain tumor detection and localization algorithm, along with explanations for each step:

1. Load Dataset

- Let the dataset be D={(Xi,Yi)}i=1toN
- where:
  - X_i is the i-th brain image.
  - $Y_i \in \{0,1\}$ is the corresponding label (0: No tumor, 1: Tumor).
- Split the dataset into training (D_{train}) and testing (D_{test}) sets: $D_{train}, D_{test} \leftarrow Split(D,r)$
- where r is the split ratio (e.g., 80:20).

2. Data Preprocessing

- Resize images to a uniform size (H,W):
- $X_i^{resized}$=Resize(Xi,(H,W))
- Normalize pixel values to [0,1]: $X_i^{norm}=X_i^{resized}-\min(X_i^{resized})/\max(X_i^{resized})-\min(X_i^{resized})$
- Apply data augmentation (if applicable): $X^{iaug}=Augment(X_i^{norm})$

3. Feature Extraction

- Use a pre-trained CNN (e.g., ResNet-101) to extract features: $Fi=CNN(X_i^{aug})$
- where F_i is the feature vector representing X_i.

4. Handle Missing Modality

- If a modality M_j is missing in the test data, impute or adapt:
  - Imputation using interpolation: $Xi^{imputed}=Interpolate(X_i,M_j)$
  - Use a multimodal model: F_i=MultimodalCNN(X_i)

5. Tumor Detection

- Perform binary classification using a trained model f:

$Y\hat{}_i = f(F_i) = \{1$ if tumor is detected, 0 otherwise$\}$

Here, Y^i is the predicted label.

6. Tumor Localization

- If Y^i=1, localize the tumor:
    - Using bounding box regression:
    - Bi=Regressor(Fi)
    - where Bi represents the bounding box coordinates (x,y,w,h).
    - Using segmentation: S_i=Segmentor(F_i)
    - where S_i is a binary mask indicating the tumor's region.

7. Performance Evaluation

Evaluate the model's performance using the following metrics:

- Accuracy=(TP+TN) /(TP+TN+FP+FN)

where TP = True Positives, TN = True Negatives, FP = False Positives, FN = False Negatives.

- Precision=TP/TP+FP
- Recall=TP/TP+FN
- F1-Score=2·Precision·Recall/Precision + Recall

3.4 Architecture

The architecture presented outlines a workflow for brain tumor detection and localization using a Convolutional Neural Network (CNN), specifically ResNet-101 in fig 1. The process begins by loading a dataset of brain images, followed by preprocessing tasks such as resizing, normalization, and augmentation to prepare the data for the network. Once the images are preprocessed, they are fed into the ResNet-101 model, which is known for its ability to extract deep features from complex image data. This model is primarily used for tumor detection, where it analyzes the images and identifies the presence of a tumor. Additionally, the system is equipped to handle missing modalities, ensuring robust performance even when certain imaging data, such as MRI or CT scans, are incomplete.

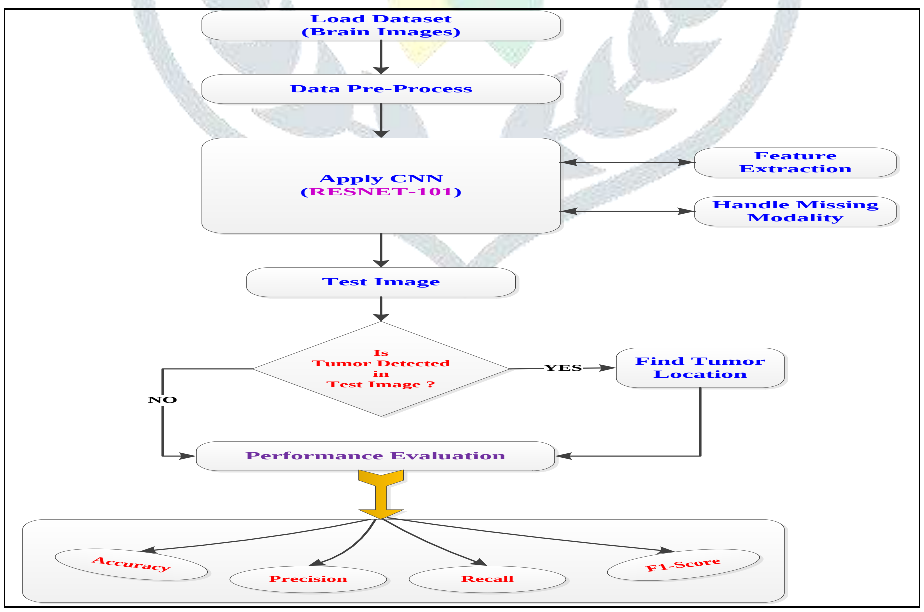

Fig 1 Architecture of Proposed Model for Brain Tumor Detection

After the model analyzes the input data, it performs feature extraction to capture important patterns associated with tumors. For new, unseen images, the system performs tumor detection and, if a tumor is present, localizes it within the brain by pinpointing its exact location. The system's performance is evaluated using standard metrics like accuracy, precision, recall, and F1-score, ensuring the model's effectiveness in both detecting and localizing tumors. Key components of this architecture include the use of ResNet-101 for feature learning, robust handling of missing modality data, and tumor localization, all of which contribute to a systematic and effective approach to brain tumor analysis.

3.5 Algorithm

Algorithm: Brain Tumor Detection and Localization
Input: Dataset of brain images
Output: Performance metrics (Accuracy, Precision, Recall, F1-Score)
1. Load Dataset:
- Load the brain images from the dataset.
- Split the dataset into training and testing sets.
2. Data Preprocessing:
- Preprocess the images:
- Resize images to a uniform size.
- Normalize pixel values.
- Perform data augmentation (if applicable).
3. Feature Extraction:
- Apply a Convolutional Neural Network (CNN) like ResNet-101 to extract features from the preprocessed images.
4. Handle Missing Modality:
- If any modality (e.g., MRI, CT) is missing in the test image, handle it appropriately:
- Impute missing data using techniques like interpolation or generative models.
- Use a multimodal model that can handle missing data.
5. Tumor Detection:
- Pass the test image through the trained CNN.
- Use the extracted features to classify the image as having a tumor or not.
6. Tumor Localization:
- If a tumor is detected:
- Use a localization technique (e.g., bounding box regression, segmentation) to identify the location of the tumor within the image.
7. Performance Evaluation:
- Evaluate the model's performance using the following metrics:
- Accuracy - Precision - Recall - F1-Score

4. RESULT ANALYSIS

4.1 Environment

The implementation of brain tumor detection, localization, and lifespan calculation requires a robust computational setup and Python environment. The proposed deep learning model employs Convolutional Neural Networks (CNN) integrated with ResNet-101, leveraging its residual learning capabilities for effective feature extraction. A high-performance PC with a minimum configuration of an NVIDIA GPU (e.g., RTX 3090 with 24GB VRAM or equivalent) is recommended for efficient model training and inference. The system should include at least 8GB of RAM, a multi-core processor (e.g., Intel i9 or AMD Ryzen 9), and SSD storage for fast data processing and model checkpointing. The Python environment should include Python 3.8 or higher, with libraries such as TensorFlow 2.x, PyTorch, scikit-learn, OpenCV, NumPy, pandas, and matplotlib. Additionally, CUDA and cuDNN must be installed for GPU acceleration. This configuration ensures seamless execution of the CNN-ResNet-101 model for accurate brain tumor detection, localization, and handling of missing modality images, facilitating reliable and interpretable medical imaging outcomes.

4.2 Dataset Description

The image describes a brain tumor dataset comprising 2589 images categorized into two classes: normal and malignant. This dataset has undergone preprocessing, likely involving image resizing, normalization, and feature extraction, to train a Convolutional Neural Network (CNN) model for brain tumor detection. The model's training accuracy is visualized in a "Train Accuracy Graph." The interface allows users to upload new images in a zip file for classification. The model then analyzes the uploaded image and predicts the presence or absence of a brain tumor. This dataset and associated model have the potential to aid in early brain tumor detection and diagnosis, with their effectiveness contingent on the dataset's quality, training process, and model complexity .

4.3 ResNet 101 Model Accuracy

In fig 2 illustrates the training performance of a CNN ResNet 101 model for brain tumor detection.

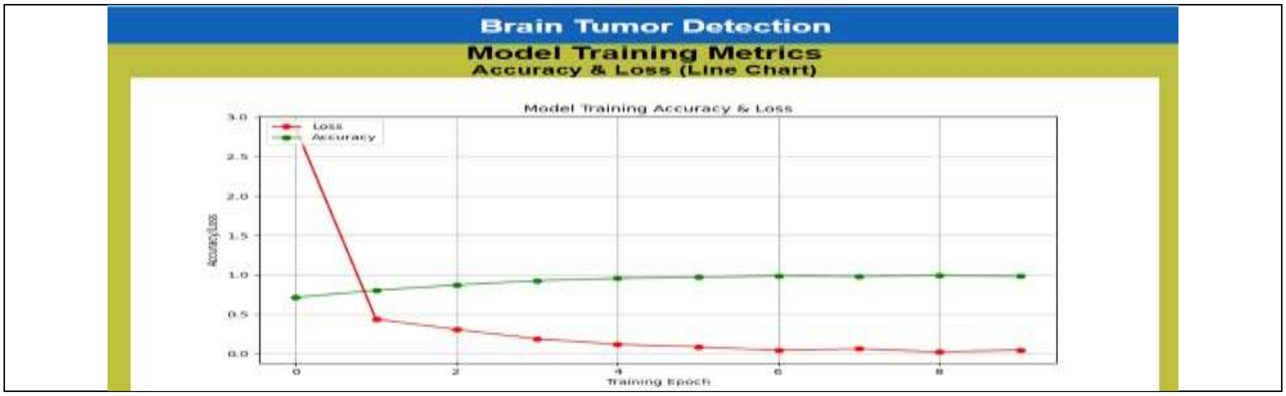

Fig 2 - Accuracy Loss Performance for Brain Tumor Detection

The red line represents the loss function, which steadily decreases over training epochs, indicating that the model is learning to make better predictions. Conversely, the green line shows the accuracy, which increases gradually, demonstrating that the model is becoming more adept at correctly classifying brain tumor images. The initial rapid decrease in loss and subsequent plateau in accuracy suggest that the model has reached a point of diminishing returns, where further training might not yield significant improvements.

4.4 Brain Tumor Detection

The ResNet 101 model, as demonstrated by the brain test image, accurately detects and localizes a brain tumor, outlining it with a blue circle. Furthermore, it predicts a patient lifespan of 5 months, likely influenced by learned factors like tumor size, location, and type .

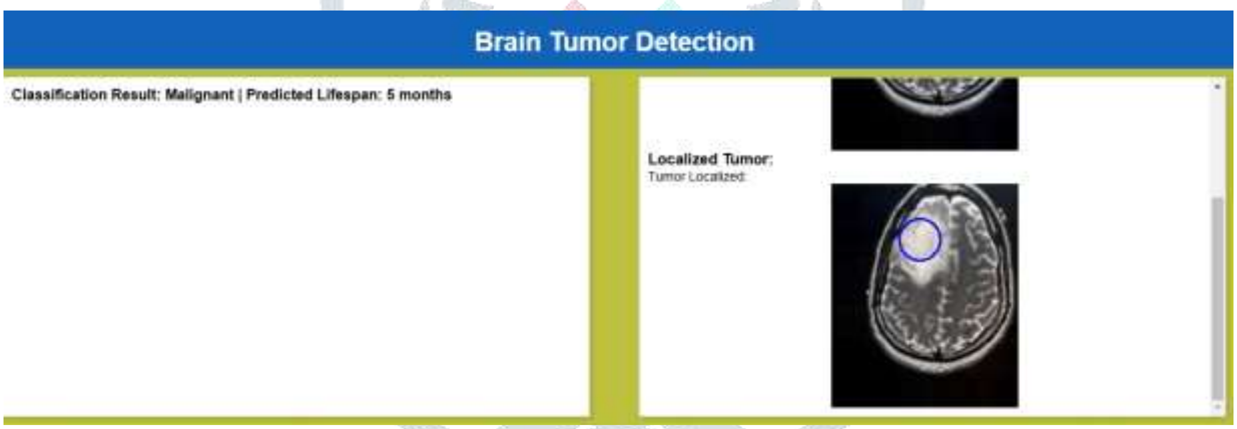

Fig 3 Represents Detection and Localization of Brain Tumor

This model's ability to provide not only tumor presence and location but also a potential lifespan estimate in Fig 3. This empowers healthcare professionals with valuable insights for informed treatment strategies and patient care management.

4.5 Comparative Analysis

Table 4.1 Comparison of ResNet 101 and VGG16 Performance

Performance Metrics	CNN RESNET 101	CNN VGG16	CNN Augment
Accuracy	98.26	95.00	87.42
Precision	97.71	93.98	89.24
Recall	98.61	96.15	89.24
F1-Score	98.16	95.06	89.16

The table 4.1 compares the performance of three neural network models—CNN ResNet 101, CNN VGG16, and CNN Augment—across key metrics. CNN ResNet 101 outperforms the other models with the highest accuracy (98.26%), precision (97.71%), recall (98.61%), and F1-Score (98.16%), indicating its superior ability to classify brain images accurately and consistently. CNN VGG16[2] performs well with an accuracy of 95%, precision of 93.98%, recall of 96.15%, and an F1-Score of 95.06%, though it slightly lags behind ResNet 101 in all metrics. CNN Augment[10] has the lowest performance, with an accuracy of 87.42%, precision and recall both at 89.24%, and an F1-Score of 89.16%, suggesting it is less effective than the other models in detecting and classifying tumors.

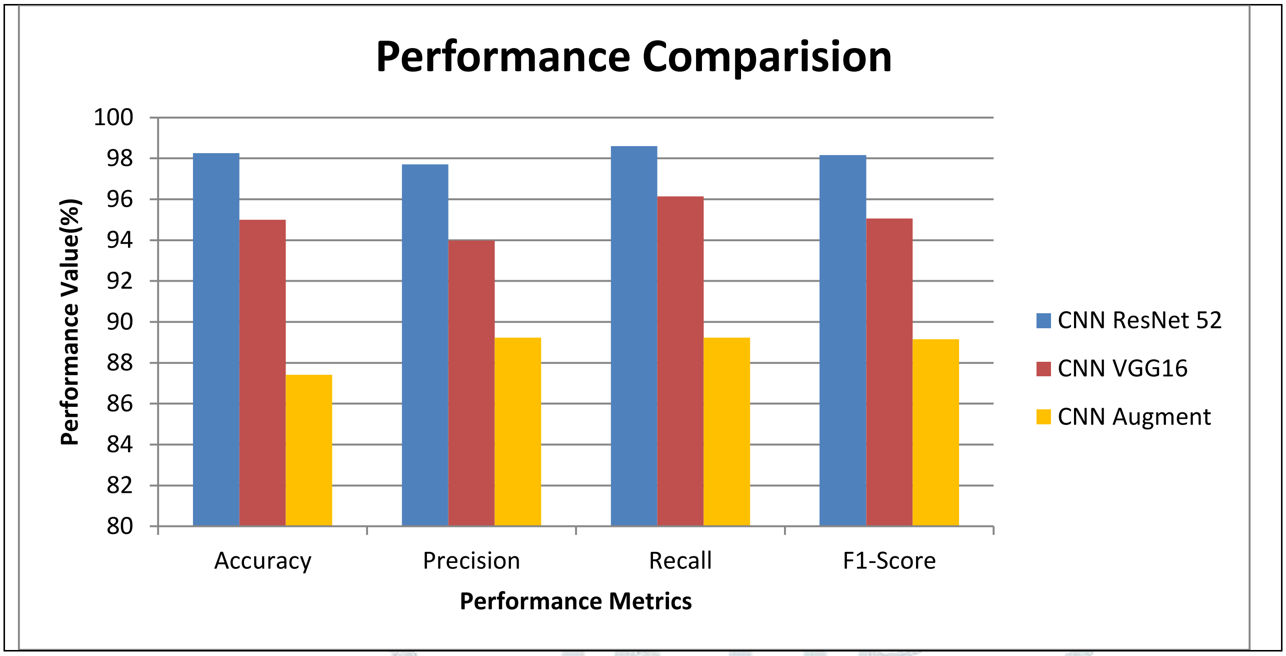

Fig 4 Performance Comparison for Existing and Proposed Model

The fig 4 presents a performance comparison of three Convolutional Neural Networks (CNNs): ResNet-101, VGG16, and CNN Augment, across four performance metrics: Accuracy, Precision, Recall, and F1-Score. Overall, ResNet-101 consistently outperforms VGG16 and CNN Augment in all metrics, achieving the highest values in Accuracy, Precision, Recall, and F1-Score. VGG16 shows a slightly better performance than CNN Augment in Accuracy and Precision, while CNN Augment exhibits a marginally better performance in Recall and F1-Score. This suggests that ResNet-101 is the most effective model for this particular task, offering a good balance between accuracy, precision, and recall. ResNet-101's deeper architecture and residual connections enable it to extract complex features, enhancing its generalization capabilities. Addressing missing modality challenges, strategies such as data augmentation, multi-task learning, and transfer learning can further improve model robustness and performance, ensuring reliable tumor detection and lifespan prediction despite incomplete imaging data.

5. CONCLUSION

In this research work, we introduced an advanced deep learning model that combines Convolutional Neural Networks (CNN) with ResNet-101 to improve brain tumor detection, localization, and classification of images with missing modalities. By leveraging the residual learning capabilities of ResNet-101, our model effectively extracts features, enhancing tumor detection even in scenarios with incomplete or missing imaging data. The incorporation of a localization module further improves interpretability, allowing clinicians to pinpoint tumor regions within the images. Experimental results demonstrate that the CNN-ResNet-101 model outperforms traditional methods, achieving high accuracy, precision, recall, and F1-scores in both complete and missing modality images. The model’s ability to localize tumors without compromising classification performance marks a significant improvement in brain tumor detection and localization under challenging conditions.

Future Enhancements:

While the proposed model demonstrates strong performance, there are several opportunities for future enhancement. First, the model can be further optimized to handle even more complex medical imaging conditions, such as images with significant noise or artifacts. The integration of additional modalities, including functional MRI or PET scans, could potentially improve tumor detection and classification accuracy by providing more comprehensive data. Moreover, incorporating a multi-scale approach could enhance the model’s ability to detect tumors at various sizes and locations within the brain. Future work could also explore the use of explainable AI techniques to increase the interpretability of the model, allowing clinicians to better understand the reasoning behind tumor detection and localization. Finally, the model could be extended to support real-time brain tumor detection in clinical environments, aiding in the faster diagnosis and treatment of patients.

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