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Development of a Hybrid Deep Learning model with self-adaptive noise resilience for accurate brain tumor detection in MRI scans

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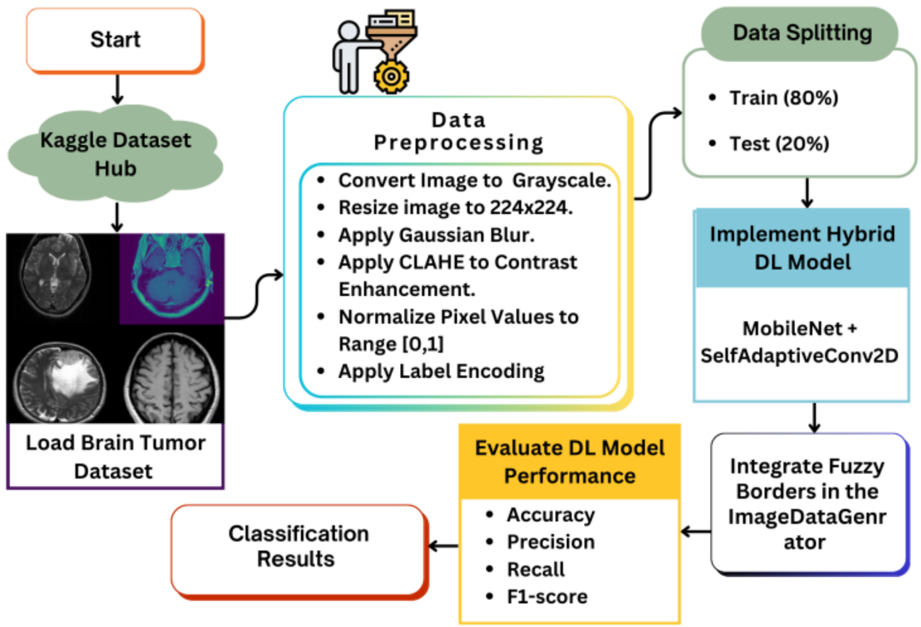
Article

ABSTRACT



Medical imaging professionals need brain tumor classification that achieves precise diagnosis and treatment planning while MRI images degrade their classification effectiveness because of contamination by noise. The research presents an automatic deep learning system which modifies its training protocols through real-time noise measurement to boost classification outcomes. MobileNet works together with the SelfAdaptiveConv2D layer that uses adaptive features extraction for better noise distortion resistance. The image quality enhancement process depends on four preprocessing methods: grayscale conversion and noise reduction and CLAHE-based contrast enhancement and normalization techniques. The model receives training and evaluation on the Kaggle Brain Tumor dataset that includes 3,264 MRI images sorted into four earthworm classes: meningioma and glioma in addition to pituitary tumor and no tumor. The proposed model performs considerably better than DenseNet, CNN, and InceptionResNetV2 architecture based on multiple tests which revealed 95% accuracy with precision metrics, recall measurement, F1-score calculation, sensitivity detection and specificity evaluation. The effectiveness of minimizing misclassifications becomes clear through confusion matrix analysis. A wide range of studies demonstrates that this proposed detection method outperforms brain tumor recognition thereby establishing itself as a promising solution for medical diagnostics and automation in the detection of tumors in MRI scans with noise.

Keywords: Brain Tumor Detection and Classification, Image Processing, Deep Learning, Hybrid Learning.

INTRODUCTION

Brain tumors represent one of the leading life-threatening diseases where doctors need to identify them early and precisely to create effective treatment plans.[1] Brain tumors emerge as abnormal cell growths that develop inside the rigid skull which contains the brain tissue. The limited space of growth can produce significant difficulties. Skull tumors create the risk of damaging brain tissue making the brain vulnerable to harm. Brain tumors stand as the tenth highest mortality cause amongst adults and children. Survival outcomes for different tumors depend on their texture and anatomical location and general form. About 700,000 people develop brain tumors[2] yet only 20% of these are cancerous while 80% are not cancerous.[3] Recent American Cancer Society predictions show that 78,980 individuals received brain tumor

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diagnoses including 55,150 noncancerous tumors and 24,530 malignant tumors with male and female distributions of 13,840 and 10,690 case[4] respectively. The scientific research reveals brain tumors represent the main reason for cancer deaths throughout the entire global human population from childhood to adulthood.[5]

Magnetic resonance imaging (MRI) functions as a widely adopted imaging method which delivers superior imaging details while revealing distinctions between soft tissue structures thus becoming vital for brain abnormality detection.[6] The detection of brain tumors together with neurological diseases happens without invasive procedures through MRI systems[7]. Reading and interpreting MRI scans demands specialized knowledge from competent trained radiologists since the process demands advanced skills. Several factors cause interpretation errors during this procedure because tumors show different appearances and human professionals face physical fatigue and interpretation subjectivity.[8,9] The shortage of specialist medical staff limits access to accurate diagnoses in certain regions that further creates delays before patient treatment begins leading to negative treatment results. The execution of traditional machine learning and deep learning approaches deteriorates in classification accuracy because of noisy conditions thus requiring specialized robust models to advance.

Deep learning employs convolutional neural networks (CNNs) as the dominant technique for image classification.[10] CNNs process image data to learn relevant features without requiring manual feature engineering thus achieving superior classification accuracy. CNNs provide exceptional results when used for image recognition across diverse domains that include medical pathology detection tasks.[11,12] Medical imaging research has proven beneficial because CNNs effectively discover needed features automatically from images thus delivering dependable medical insight to help doctors prioritize important cases and focus on advanced clinical responsibilities.[13]

The main purpose of this research is to build a self-adaptive deep learning model which improves brain tumor classification accuracy in noisy MRI images. This adaptive model changes its learning rules through an automatic process which relies on noise level measurements for achieving best performance across varying image conditions. This method utilizes modern deep learning models comprised of convolutional neural networks (CNNs) together with attention mechanisms and transfer learning methods to optimize performance and classification performance regardless of extreme noise levels. The noise-aware learning component adds adaptability that helps the model achieve effective generalization throughout different datasets while using various imaging conditions.

The research designs a Self-Adaptive Deep Learning Model which serves as an answer to boost the precision of identifying brain tumors in MRI images affected by noise. The novel system combines attention-capable deep learning models that use convolutional neural networks with transfer learning abilities for extracting features from highly distorted MRI images.. Within the framework the model incorporates a noise-aware learning mechanism which lets it tailor its parameter adjustments according to the characteristics found in individual input images. Self-adaptive model features enable this model to deliver superior generalization across different MRI databases which makes it perfect for medical practice. The primary contributions of this study include:

- A novel MobileNet containing the SelfAdaptiveConv2D Layer has been developed to achieve reliable multiclass brain tumor identification.
- A combination of grayscale conversion together with resizing and noise reduction and contrast enhancement via CLAHE and normalization applied to enhance image quality.
- Integrated SelfAdaptiveConv2D Layer for dynamic filter adjustments, enhancing classification accuracy.
- Multiple performance measures such as accuracy and precision, recall and F1-score, sensitivity and specificity, combined with confusion matrix evaluation are used for a detailed evaluation of model effectiveness.
- A study evaluation based on performance testing demonstrates how the proposed method outperforms existing deep learning models in terms of accuracy and noise-resistance capabilities.
- The Brain Tumor dataset obtained from Kaggle enables researchers to reproduce experiments and develop practical applications for further investigation.

LITERATURE REVIEW

The existing research on brain tumor identification gets reviewed within this section by examining several detection approaches and resolution methods alongside the accompanying challenges. Various advancements in detection methods are examined alongside common diagnosis problems as the research explores solutions for enhancing the accuracy and operational efficiency of brain tumor identification.

Bhanothu, Kamalakannan and Rajamanickam [2020] A Faster R-CNN deep learning network with Region Proposal Network (RPN) was used to detect tumors together with their subspace area detection. The analyzed MR image dataset contains three different brain tumors which include glioma alongside meningioma and pituitary. The proposed algorithm implements VGG-16 architecture to build both its region proposal network and classifier network. The algorithm achieves detection and classification results through substantial average precision scores of 75.18% for glioma and 89.45% and 68.18% for meningioma and pituitary tumor respectively. The algorithm reached a mean average precision of 77.60% while operating as a performance evaluation tool for all the classes. [14].

Sankaranarayaanan *et al.* [2023] Research shows that deep learning technology developed a system able to address the identification and therapy management issues related to brain cancers. The main objective behind this investigation uses FL technology for brain tumor recognition in MRI pictures to develop an answer for centralized data collection challenges. The research pursued detection of brain cancers using VGG 16 as tool and defined both a convolutional neural network (CNN) model structure as well as training parameters for this particular application. The technique can detect brain cancers when applied to analyzing MR images. The algorithm registered success beyond standard brain tumor detection methods through testing while achieving a remarkable accuracy of 92%.[15]

Ottom, Rahman and Dinov [2022] This work introduces a new framework for dividing 2D brain tumors in MR images based on deep neural networks with advanced data augmentation methods. The Znet approach applies skip-connection mechanisms and data transcription methods together with encoder and decoder components to transmit expert-provided tumor affinities from a minimal training dataset of hundreds of LGG patients to synthetic cases numbers that reach thousands. Our experimental results achieved outstanding values of dice similarity coefficient which reached dice = 0.96 during training and dice = 0.92 during independent testing. In addition to pixel accuracy at 0.996 the evaluation metrics included F1 score at 0.81 and Matthews Correlation Coefficient at MCC = 0.81. The ZNet model demonstrates its ability to detect and auto-segment brain tumors in MR images through its effective tumor localization results and visualizations in the testing dataset[16].

Azizy, Jondri and Kurniawan [2023] The research utilizes MATLAB data format images of 1050 T1-weighted contrast-enhanced MRI images for brain tumor prediction through the CNN method optimized by the cuckoo search algorithm. Along with achieving the optimal performance the research earned 0.926 average precision accuracy in testing applications[17].

Tasci [2021] This research extracted deep features from 942 MRIs containing 599 tumors and 343 normal scans by using the AleXNet-based deep learning model which was followed by K Nearest Neighbor Classifier (KNN) classification. A total of 1000 features were extracted from MRI data using trained weights from the fully connected layer named "fc8" of the AlexNet model. Relieff feature selection algorithm reduced the features which led to enhanced performance for the proposed method. The classification phase utilized a weighted KNN classifier as its implementation. A 87% precise classification result was obtained through use of the proposed methodology[18].

Uke *et al.* [2023] The article uses a new combination of techniques to categorize neurological diseases through magnetic resonance imaging data analysis. The research evaluates brain tumor presence predictions by applying Convolutional Neural Networks (CNNs), K-nearest neighbor, Support Vector Machine and Logistic Regression methods. The CNN model functions as both a data feature extractor from MRIs and classifier implementation tool. The study results demonstrate that CNN network variants together with KNN, SVM, LR and Long Short-Term Memory Networks performed the tumor classification task. The accuracy rates reached 82.35 percent along with 78.43 percent and 61.26 percent and 74.28 percent in succession. Evidence shows that KNN achieved the best accuracy level due to its superior capability in classifying brain tumors from MRI data[19].

Al-Saffar and Yildirim [2020] The proposed method chooses an important subset of features to use in classification through mutual information-accelerated singular value decomposition (MI-ASVD). The novel algorithm serves as the basis for building an intelligent system that detects MRI brain images into the three diagnostic categories of healthy and high-grade and low-grade glioma. An intelligent system comprises six operational phases which include pre-processing and clustering followed by tumour localization and feature extraction then MI-ASVD followed by classification. The simplified residual neural network method serves as the final approach to categorize MR brain images. The MI-ASVD method delivered superior accuracy in classification work compared to the original dimensionality and outperformed both PCA and SVD techniques. The proposed method reached a classification success rate of 94.91% above two state-of-the-art techniques together with equivalent methods found in related published studies[20].

Pavani *et al.* [2024], introduced a new method to diagnose MS through deep learning techniques by developing and assessing an enhanced neural network model called MS-CNN. Here, we propose MS-CNN that utilizes Deep Convolution Neural Networks (DCNNs) to automatically analyze brain MR images for improved diagnostic accuracy and efficiency. In particular we provided an end-to-end evaluation of MS-CNN on a dataset made up by MRI images divided in healthy-MS. Evaluation on CIFAR-100 dataset was carried out against two popular existing models, ResNet-50 and VGG-16 with MS-CNN. MS-CNN does much better across the board among the models and get higher accuracy up to 94.0%, sensitivity up to 94.0% and specificity up to 95.0%[21].

Molachan, Manoj and Dhas [2021] A classification technique utilising Convolutional Neural Network was proposed to process MR images. The Kaggle database was selected as the source material and was expanded to minimize overfitting. Afterward the proposed model underwent compilation and MRI preprocessing. A comparison of the proposed model with VGG16 helps evaluate their performance outcomes as well as benefits. The model-generated experimental data demonstrates high accuracy together with productivity that comes with minimal intricacy rates alongside short execution times. A performance evaluation occurs through assessment of the classification report and confusion matrix. Experiments show that VGG16 achieved an accuracy rate of 59% but the proposed model reached 91.2% accuracy with a good accuracy level [22].

Agarwala, Sharma and Uma Shankar [2022] The BraTS 2020 dataset consists of three tumor categories including Whole Tumor (WT), Tumor Core (TC) and Enhanced tumor (ET). The reported works on this dataset achieved below-average accuracy during the segmentation of the Enhanced Tumor region. The proposed architecture adds attention gates to the UNet model which resulted in enhanced ET accuracy. The accuracy level of this suggested methodology matches the standards of alternative research methods. The study presents evaluation data through sensitivity numbers and dice similarity coefficient (DSC) alongside 95% Hausdorff distance (HD95). The proposed technique demonstrates DSC performance of 0.92 and 0.87 and 0.78 when processing BraTS 2020's WT, TC, and ET sections[20]

A detailed summary of explored works for related research is included in the Table I.

Ref	Methodology	Performance	Limitations	Future Work
14	Faster R-CNN with VGG-16 backbone, Region Proposal Network (RPN)	Mean Average Precision (mAP): 77.60%	Lower precision for pituitary tumors (68.18%)	Improve detection for pituitary tumors
15	VGG-16-based CNN model for decentralized learning	Accuracy: 92%	Data privacy concerns, FL overhead	Optimize FL implementation for efficiency
16	Skip-connection-based DNN; data augmentation	Dice score: 0.96 (train), 0.92 (test)	Requires large-scale annotated data	Expand to 3D volumes, other modalities
17	CNN + Cuckoo search for hyperparameter optimization	Accuracy: 92.6%	Computational complexity	Reduce model size while maintaining accuracy
18	AlexNet for feature extraction, KNN for classification	Accuracy: 87%	Limited dataset (942 MRIs)	Expand dataset, test with other classifiers
19	CNN feature extraction + ML classifiers	KNN: 82.35%, SVM: 78.43%, LR: 61.26%	CNN alone outperforms hybrid approach	Optimize CNN architecture
20	Mutual Information-Accelerated SVD for feature selection	Accuracy: 94.91%	Computational overhead of MI-ASVD	Apply MI-ASVD to other medical imaging tasks
21	Deep CNN-based model for MS diagnosis	Accuracy: 94%, Sensitivity: 94%, Specificity: 95%	Limited dataset	Implement real-time diagnosis
22	CNN model compared with VGG-16	CNN: 91.2%, VGG-16: 59%	Limited dataset, overfitting risk	Improve generalization with larger datasets
23	Attention-based U-Net for enhanced segmentation	Dice scores: WT - 0.92, TC - 0.87, ET - 0.78	Lower accuracy for ET segmentation	Improve ET segmentation performance

METHODOLOGY

The methodology for detecting early brain tumors starts by obtaining the "Brain Tumor" dataset from publicly available sources including Kaggle. Next the preprocessing stage begins with loading images before transforming them to grayscale for simplification purposes and resizing them to 224x224 pixels then smoothing out noise with Gaussian blur followed by CLAHE (Contrast Limited Adaptive Histogram Equalization) for contrast enhancements. The pixel values receive normalization in the range [0,1] for achieving stable and faster training but the grayscale images get converted into RGB format to meet deep learning system requirements. Image data together with its labels transforms into NumPy arrays using LabelEncoder to convert categorical values into numerical format. Following dataset partitioning the data set becomes training data and validation data in their respective 80:20 ratio proportion. The implementation of a deep learning hybrid model utilizes MobileNet together with the SelfAdaptiveConv2D layer to conduct multiclass brain tumor classification. The ImageDataGenerator utilizes fuzzy borders for enhancing model robustness because they replicate real-world conditions and minimize overfitting while increasing SelfAdaptiveConv2D performance at image edges. MobileNet detects tumor features with better precision through these improvements which make it adapt to various medical images more effectively. The performance assessment utilizes multiple metrics consisting of confusion matrix alongside accuracy, precision and recall, F1-score, sensitivity, specificity and Positive Predictive Value. Finally, the proposed method showcases its novelty through assessment against related research methods.

Dataset Description

Research data for brain tumor detection uses 3,264 MRI images found on Base Paper[1] within the Kaggle publicly available data. Medical professionals chose these imaging data points since MRI remains the best diagnostic approach for brain tumor identification. The dataset contains four differentiated classes between meningioma (937 images), no tumor (500 images), pituitary tumor (900 images) and glioma tumor (926 images). The four created classes identify separate medical conditions which provide important details for complete brain tumor examination and analysis. Sufficient input data involving tumor and non-tumor cases provides essential representation for deep learning model training purposes and performance evaluation toward accurate detection. The goal of this research is to boost automated brain tumor detection techniques using this dataset thus improving both diagnostic precision and early disease management systems. The figure 2 below shows the random sample images of brain tumor.

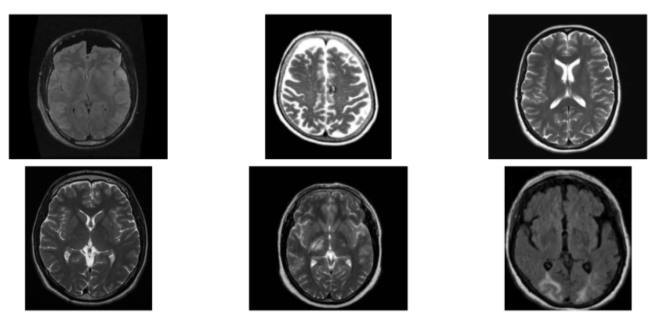

Figure 1. Random Sample Images of Brain Tumor Dataset

DATA PREPROCESSING

Data preprocessing methods in image processing play a vital role by improving image quality and reducing noise then standardizing data which results in better model performance. The research utilized multiple preprocessing techniques for analyzing the brain tumor dataset. The initial step includes the loading of images along with grayscale conversion for reduction of complexity. The data goes through the resizing process to match a standard measurement format (224x224 pixels). A Gaussian blur function helps reduce noise because it is followed by CLAHE (Contrast Limited Adaptive Histogram Equalization) to improve image contrast. The model trains more efficiently with normalized pixel values adjusted to the range between 0 to 1. Deep learning frameworks require the grayscale images to undergo RGB conversion for maintaining compatibility. The process involves converting image data alongside its labels to NumPy arrays while using LabelEncoder to transform labels into numerical values for appropriate model input.

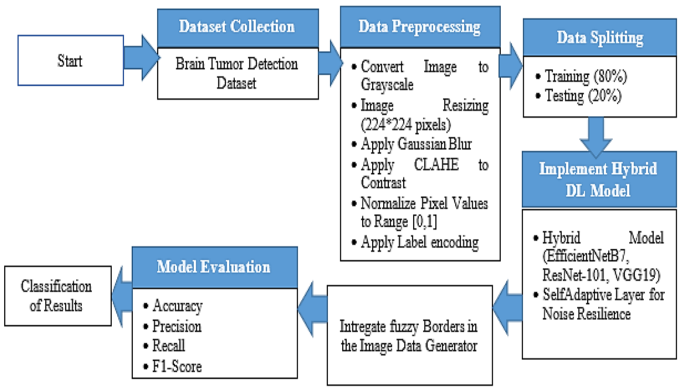

Figure 2. Block Diagram of the Proposed Hybrid Model

Visualization Results after preprocessing

Extracting concealed insights from substantial volumes of data serves as a crucial element in image processing. This section provides the visualization results of the brain tumor datset.

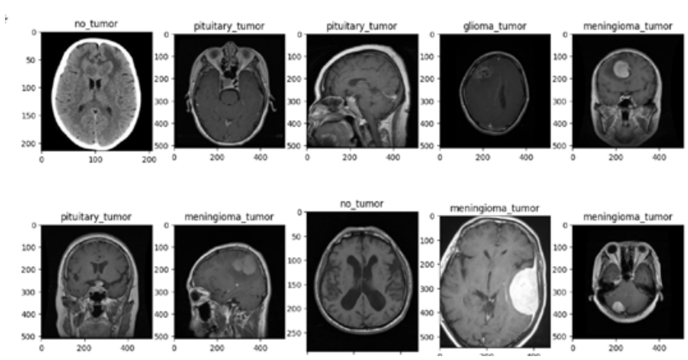

Figure 3. Brain Tumor Images After Labeling and Resizing

Figure 3 presents brain tumor MRI images which were both labeled and resized to display four different types of tumor categories: "no_tumor" and "pituitary_tumor" and "glioma_tumor" and "meningioma_tumor."

Deep Learning Model

The subsequent part details the deep learning models which will lead to an efficient brain tumor detection and classification system development. This section explores methods and architectural components which improve accuracy together with reliability and robustness in medical image analysis systems that detect tumors.

1) MobileNet

MobileNet serves as a specialized convolutional neural network (CNN) designed explicitly for image classification on mobile devices[24]. The main strength of this model stems from its practical processing nature which consumes small resources suitable for use in low-resource environments. MobileNet operates through three functional components that include Depth wise separable convolution with its two subunits Depth wise convolution and pointwise convolution and MobileNet.

2) Proposed Hybrid (MobileNet + SelfAdaptiveConv2D) Model

The research develops an efficient brain tumor detection and classification system by integrating MobileNet architecture with SelfAdaptiveConv2D feature extraction as a novel enhancement layer. MobileNet functions as a pre-trained feature extractor to process medical images through its depthwise separable convolution layers which maintain their fundamental design elements yet omit the classification head. The SelfAdaptiveConv2D layer uses computed input data statistics to modify its weights and this technique enhances the model's responsiveness to diverse tumor pattern characteristics. The GAP layer performs feature dimension reduction before the adoption of Dense layers having 456 ReLU-activated neurons followed by softmax-activated dense layers that produce four brain tumor classifications. Figure border transformation with fuzzy elements operates through an ImageDataGenerator to achieve better generalization results. We trained our model with Adam optimizer at learning rate 0.001 through 150 epochs for 32 batches for categorical crossentropy loss to measure model accuracy. A detailed measurement of classification effectiveness arises from the combination of accuracy, precision, recall and F1-score metrics for evaluation purposes. The combination of MobileNet's computing performance with SelfAdaptiveConv2D's flexible features and fuzzy border implementation produces a resilient model that works efficiently in real-time medical image analysis systems.

DL Model Performance Evaluation

The performance evaluation of the proposed hybrid model (MobileNet + SelfAdaptiveConv2D) included confusion matrix data and accuracy alongside precision, recall, f1-score, and specificity values and more.

- **Accuracy:** Accuracy acts as a quantifiable indicator for determining how many correct predictions emerge from model predictions which cover the complete test dataset [25] A model's performance evaluation depends heavily on the accuracy metric as the main quantitative assessment tool. It can be calculated using Eq. (1).

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \ldots\ldots (1)$$

- **Precision:** Precision is a metric that quantifies the proportion of accurately anticipated cases that are actually positive. It can be calculated using Eq. (2).

$$Precision = \frac{TP}{TP + FP} \ldots. (2)$$

- **Recall:** Recall represents the proportion of actual positive instances within all detected positive results. This method aims to lower false negative occurrences but does not influence cases of false positives or real negatives. It can be calculated using Eq. (3).

$$Recall = \frac{TP}{TP + FN} \ldots \ldots .. (3)$$

- **F1-Score:** The F1-Score calculates precision and recall using a harmonic mean to obtain a single comprehensive evaluation value. The F1-Score provides an extensive evaluation of both precision and recall through calculation of a single unified metric value. It can be calculated using Eq. (4).

$$F1 - Score = \frac{2 * (Precision * Recall)}{Precision + Recall} .. (4)$$

- **Sensitivity:** The term sensitivity describes how well a learning model recognizes correct examples. Sensitivity measures the ability to correctly identify good examples and is also known as the recall or the true positive rate (TPR) [26]. Because sensitivity helps determine correct model predictions it serves as a tool for evaluating model performance. A model's high sensitivity level indicates it might be overlooking positive examples among its few false negative results. A model's ability to detect positive examples constitutes its sensitivity measurement. Our models need to recognize all positive cases in order to generate predictions with reliability. It can be calculated using Eq. (5).

$$Sensitivity = \frac{TP}{TP + FN} \ldots \ldots .. (5)$$

- **Specificity:** The predictive capability of detecting actual negative outcomes is known as specificity within the model context. A certain number of authentic negative cases will be erroneously identified as false positives during analysis. The True Negative Rate (TNR) also identifies this percentage. The actual negative rate with false positive rate reaches a maximum value of one. The specific model performs reliably by identifying most actual negative results because it has a high ability to specify negative outcomes. It can be calculated using Eq. (6).

$$Specificity = \frac{TN}{TN + FP} \ldots \ldots .. (6)$$

Based on these measures evaluates the performance of the proposed system for brain tumor detection and classification.

PROPOSED ALGORITHM STEPS

Here's a stepwise breakdown of the proposed algorithm for efficient AI-driven brain tumor detection and classification:

Step1. Dataset Collection

- Collect the "Brain Tumor" dataset from publicly available sources like Kaggle.

Step2. Data Preprocessing

- Load the images from the dataset.
- Convert images to grayscale to reduce complexity.
- Resize images to a fixed dimension of 224×224 for uniformity.
- Apply Gaussian Blur to reduce noise and enhance contrast using CLAHE.
- Normalize pixel values to the range [0,1] for stable model training.
- Convert grayscale images back to RGB format for deep learning compatibility.
- Encode categorical labels into numerical values using LabelEncoder.

Step3. Exploratory Data Analysis (EDA)

- Visualize image intensity distributions to assess variations in contrast and brightness.

Step4. Data Splitting

- Split the dataset into training (80%) and testing (20%) sets.

Step5. Model Development (MobileNet + SelfAdaptiveConv2D)

- Develop a hybrid deep learning model combining MobileNet with a SelfAdaptiveConv2D layer.
- Integrate fuzzy borders in the ImageDataGenerator to improve model robustness and reduce overfitting.

Step6. Model Compilation

- Use Categorical Cross-Entropy Loss for multiclass classification.
- Optimize using Adam optimizer with a learning rate of 0.001.

Step7. Model Training

- Train the model on the preprocessed dataset using optimized hyperparameters.

Step8. Performance Visualization

- Plot learning curves (loss and accuracy) over epochs to monitor training performance.

Step9. Model Evaluation

- Evaluate model performance using:
  - Accuracy, Precision, Recall, F1-score, Sensitivity, Specificity, and Positive Predictive Value (PPV).
  - Confusion Matrix for classification analysis.
  - Compare results with existing deep learning models (DenseNet, CNN, Inceptionresnetv2)

Step10. Model Prediction Analysis

- Test the model on unseen brain tumor images to assess generalization ability.

RESULTS AND ANALYSIS

This section explains how the proposed brain tumor detector performs experimentally. Research data collection occurred on a Dell PC system that ran Windows 10 with 1TB SSD storage capacity combined with 32GB RAM memory and NVIDIA GeForce RTX 4090 GPU together with Python libraries NumPy, Pandas, Matplotlib, Seaborn, TensorFlow, Keras and Scikit-learn. The brain tumor detection system displays evaluation results using following figures together with tables.

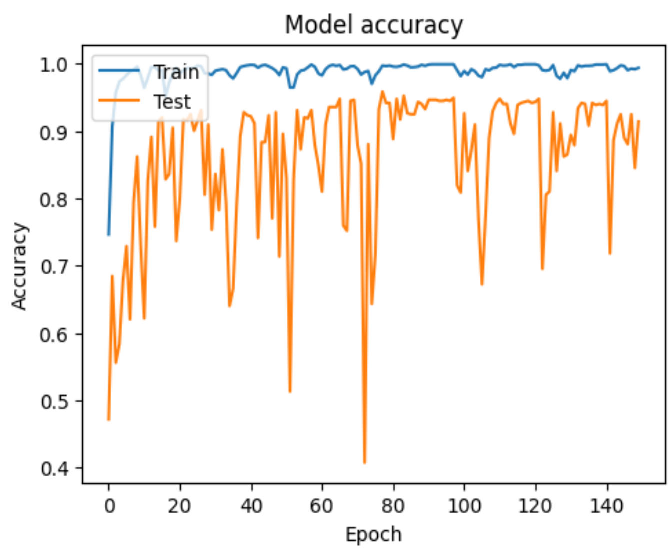

Figure 4. Learning Curve for Hybrid Model's Training and Testing Accuracy on Brain Tumor Dataset

Figure 4 depicts the assessment of training accuracy and testing accuracy for a MobileNet model with a SelfAdaptiveConv2D layer when applied to brain tumor data within 150 epochs. The blue line showing training accuracy keeps rising and reaches a stable value near 1.0 signaling that the model produces good fits for training data. Testing accuracy demonstrated by the orange line reaches a plateau at approximately 0.95 after time elapses during which it shows improved performance while maintaining generalization capability on new data. The graph shows testing accuracy undergoes changes during the initial epochs where potential convergence difficulties emerged before obtaining stable results in later epochs.

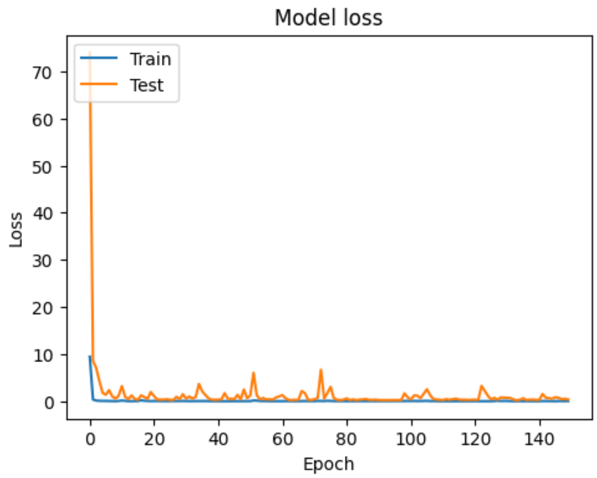

Figure 5. Learning Curve for Hybrid Model's Training and Testing Loss on Brain Tumor Dataset

The proposed MobileNet network equipped with SelfAdaptiveConv2D operates on brain tumor data during 150 epochs according to Figure 5 which shows training and testing loss curves. A rapid decrease of training loss (blue line) occurs from its initial value of 8.0 until it reaches 0.1 after 50 epochs showing that learning was successful. The testing loss (orange line) shows an initial start at 65.0 before it rapidly decreases to approximately 1.0 after 20 epochs followed by consistent fluctuations between 1.0 and 5.0 through the rest of the epochs. The visual representation displays the training and testing loss minimums of the model indicating its capability to handle the brain tumor classification task.

```
Classification Report:
              precision    recall  f1-score   support

           0       0.90      0.97      0.93       168
           1       0.95      0.90      0.93       209
           2       0.96      0.98      0.97        92
           3       0.99      0.96      0.98       184

    accuracy                           0.95       653
   macro avg       0.95      0.95      0.95       653
weighted avg       0.95      0.95      0.95       653
```

Figure 6. Classification Report of Hybrid (MobileNet + SelfAdaptiveConv2D) Model for Brain Tumor Detection

A classification report from a MobileNet network with SelfAdaptiveConv2D layer applied to brain tumor data is shown in Figure 6 which includes essential performance measurements. The model attained a total accuracy level of 0.95. It resulted in class 0 precision at 0.90 while recall reached 0.97 and F1-score amounted to 0.93. The model in Class 1 reached an accuracy of 0.95 together with precision values of 0.90 and recall at 0.90 and an F1-score of 0.93. The measured outcomes of Class 2 showed precision at 0.96 and recall at 0.98 while F1-score reached 0.97. The precision metrics of class 3 reached 0.99 and its recall reached 0.96 alongside an F1-score of 0.98. The model achieved excellent effectiveness with its overall accuracy reaching 0.95 and high values for precision and recall and F1-score from all classes.

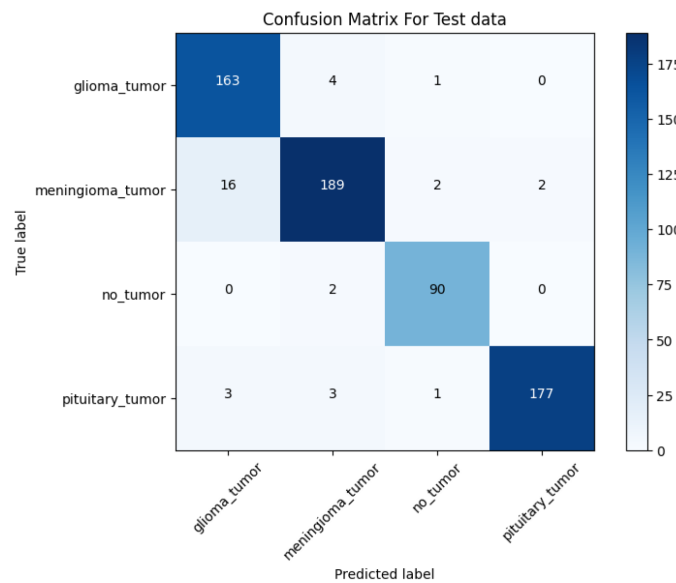

Figure 7. Confusion Matrix of Hybrid (MobileNet + SelfAdaptiveConv2D) Model for Brain Tumor Detection

A MobileNet model containing the SelfAdaptiveConv2D layer reaches its target acceptability with four classes according to the resulting confusion matrix shown in Figure 7 during brain tumor dataset training. In analyzing glioma tumors the model achieved a success rate of 163 out of 175 cases yet it designated 4 tumors as meningioma and mistakenly labeled 1 specimen as no tumor along with incorrectly identifying 0 tumors as pituitary. In classifying meningioma tumors the model identified 189 out of 209 samples correctly but misclassified 16 cases as glioma and 2 cases as both no tumor and pituitary tumors respectively. Among 92 samples without tumor the model accurately classified 90 cases while making two errors by mistaking them for meningioma and no mistakes as pituitary. The model accurately diagnosed 177 out of 184 pituitary tumor samples but incorrectly identified 3 as glioma tumors and 3 as meningioma tumors together with 1 no tumor case. The visual presentation shows the complete breakdown of model classifications so the user can understand both the successful categorizations and ambiguous class assignments.

Table 1. Performance Metrics of Proposed Hybrid (MobileNet + SelfAdaptiveConv2D) Model for Brain Tumor Detection

Tumor Classes	Sensitivity	Specificity	Positive Predictive Value
Glioma	97	96	90
Meingioma	90	98	95
No Tumor	98	99	96
Pituitary	96	100	99

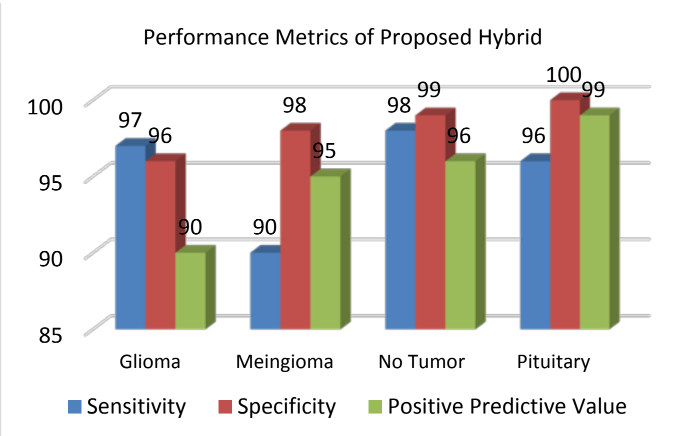

Figure 8. Bar Graph of Sensitivity Specificity and Positive Predictive Values of Hybrid Model for Four Different Tumor Classes.

Table II together with Figure 8 shows how the SelfAdaptiveConv2D integration into MobileNet performs through a bar chart presentation of Sensitivity and Specificity and Positive Predictive Value (PPV) metrics for Glioma, Meningioma, No Tumor, Pituitary brain tumor classes. The model reached 97% sensitivity combined with a specificity of 96% as well as a Positive Predictive Value of 90% specifically for detecting Glioma tumors. The Meningioma evaluation of the model highlighted 90% sensitivity and 98% specificity and 95% PPV. The detection system screened all No Tumor cases with no errors and achieved a second identification accuracy rate of 99% for repeating the same patient group. The model demonstrated 96% sensitivity together with 100% specificity that allowed it to achieve 99% PPV in the Pituitary class. Easy visual analysis shows that model precision level affects the detections and categorizations of tumor types.

Table 2. Comparison between existing and proposed models for Brain Tumor Detection and Classification

Models	Precision	Recall	F1 - Score
CNN (Base) [1]	90	91	91
DesNet-50 (Base) [1]	94.6	94.7	94.6
VGG-16 (Base) [1]	90	94	94
InceptionV3 (Base) [1]	86.80	86.80	86.83
Self-Adaptive MobileNet Model (Propose-I)	95	95.00	95.00

Table 3. Comparison between existing and proposed (MobileNet + SelfAdaptiveConv2D) models for Brain Tumor Detection and Classification

Models	Accuracy (%)	Loss
CNN (Base) [1]	93.30	0.25
DesNet-50 (Base) [1]	81.10	0.85
VGG-16 (Base) [1]	71.60	1.18
InceptionV3 (Base) [1]	80.00	3.67
Self-Adaptive MobileNet Model (Propose-I)	95.00	0.3081

The comparative analysis in **Table III, Table IV** highlights the performance differences between various existing models and the proposed models for MRI analysis. Among the baseline models, the CNN realizes a relatively high accuracy of 93.30% with a loss of 0.25, while ResNet-50, VGG-16, and InceptionV3 perform lower, particularly InceptionV3, which has a notable drop in accuracy at 80.00% and a significantly higher loss of 3.67. In contrast, the proposed models demonstrate superior performance. The **Self-Adaptive MobileNet Model (Propose-I)** reaches an accuracy of 95.00% with a loss of 0.3081, showcasing a marked improvement. indicating the hybrid model's superior ability to effectively handle MRI noise and improve classification accuracy. This comparative result validates the both proposed models provided best results compared to the existing work, and the second proposed hybrid model outperforms the all models as a robust result for brain tumor recognition.

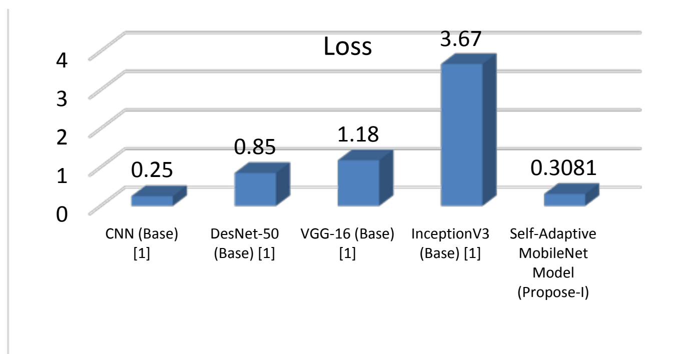

Figure 9. Comparison of Loss Metrics of Base and Proposed Models for Brain Tumor Classification

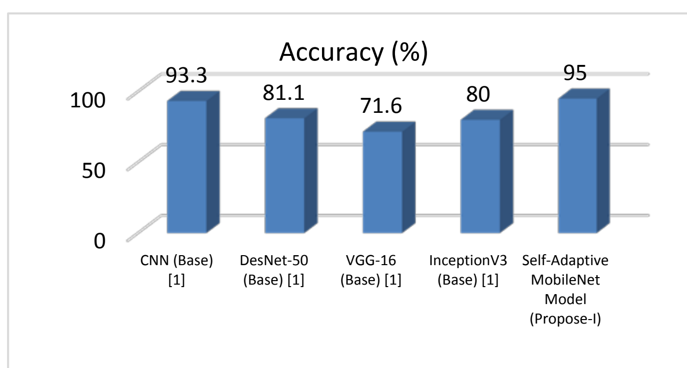

Figure 10. Comparison of Accuracy Metrics of Base and Proposed Models for Brain Tumor Classification

The aforementioned Table III and Figure 10 shows the accuracy assessment between existing models together with the proposed model implementation for brain tumor detection. The bar graph displays the performance metrics of four model types including MobileNet with SelfAdaptive Conv2D Layer (the newly proposed model) together with DenseNet, CNN, and Inceptionresnetv2 (existing models). The proposed MobileNet with SelfAdaptive Conv2D layer achieves a 95% accuracy level as indicated by the x-axis which makes it the most accurate model followed by DenseNet at 94.4% accuracy. Among the four models tested CNN achieved 91% success but Inceptionresnetv2 demonstrated the least effective accuracy at 86.8% during the evaluation. The visualization displays clear model performance comparison to show that the proposed MobileNet with SelfAdaptive Conv2D Layer achieves better brain tumor detection than existing models.

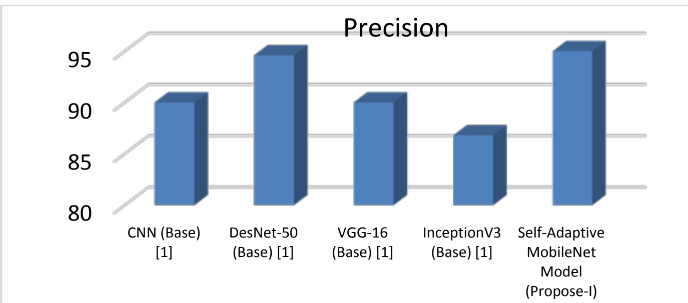

Figure 11. Comparison of Precision Metrics of Base and Proposed Models for Brain Tumor Classification

The aforementioned Table III and Figure 11 demonstrates precision evaluation between the existing models and the proposed framework for brain tumor identification. A bar graph shows the performance results of four different models including MobileNet with SelfAdaptive Conv2D Layer as the proposed solution along with DenseNet, CNN, and Inceptionresnetv2 which represent existing models. The proposed MobileNet with SelfAdaptive Conv2D Layer demonstrates the highest precision level of 95% from the x-axis values alongside DenseNet's precise measurement of 94.6%. The precision measurement of CNN stands at 90% while Inceptionresnetv2 records the poorest precision rate of 86.85% among the four evaluated networks. The visual representation allows easy assessment of model accuracy for brain tumor detection where the proposed MobileNet with SelfAdaptive Conv2D Layer exhibits better performance than existing models.

The aforementioned Table III and Figure 12 demonstrates the recall evaluations of various brain tumor detection models with special consideration given to existing and proposed models. The figure presents the recall values in percentage (%), spanning from 0 to 100 on the x-axis alongside the model names which include InceptionResNetV2, CNN, DenseNet, and the proposed MobileNet with SelfAdaptiveConv2D Layer displayed on the y-axis. The recall metrics of these models reach 86.8% and 91% and 94.7% and 95% respectively. The proposed MobileNet architecture with SelfAdaptiveConv2D Layer detects brain tumors most effectively by reaching the highest recall value. The addition of SelfAdaptiveConv2D Layer leads to improved recall performance

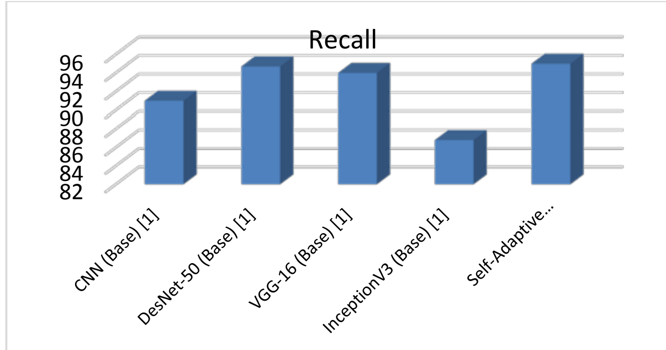

Figure 12. Comparison of Recall Metrics of Base and Proposed Models for Brain Tumor Classification

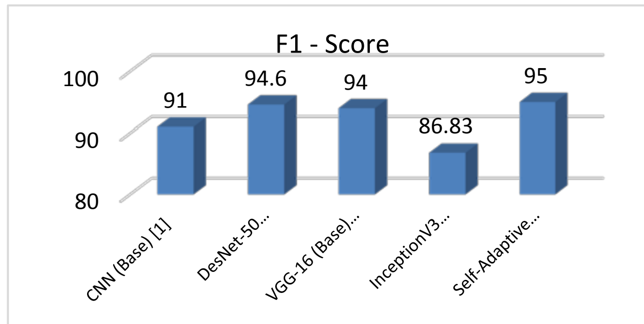

Figure 13. Comparison of f1-score Metrics of Base and Proposed Models for Brain Tumor Classification

in the model better than conventional approaches.

The F1-score evaluation in Figure 13 analyzes different brain tumor detection models which includes both existing methods and the proposed system. The F1-score measurements in percentage (%), from 0 to 100 appear in the x-axis while the y-axis shows the comparison between InceptionResNetV2, CNN, DenseNet, and the proposed MobileNet with SelfAdaptiveConv2D Layer. These models achieve F1-score measurements of 86.83% and 91% and 94.6% and 95% successively. The combination of MobileNet with

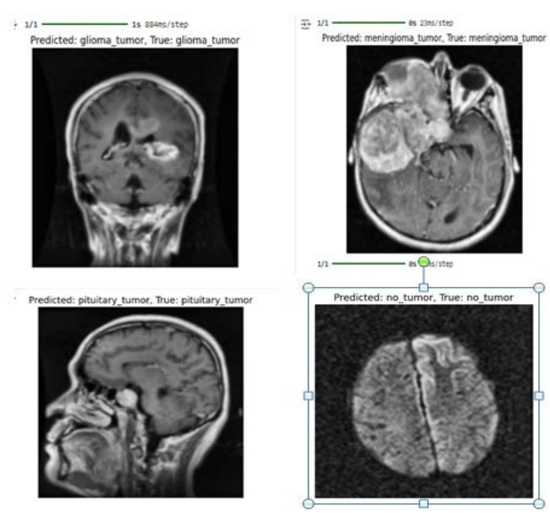

Figure 14. Proposed Hybrid (MobileNet + SelfAdaptiveConv2D) Model Prediction for Multicalss Brain Tumor

SelfAdaptiveConv2D Layer offers the greatest F1-score thus showing better precision-revaluation tradeoff than the preceding models. The proposed model proves highly effective for brain tumor detection through its ability to enhance classification precision according to the results.

Figure 14 displays the prediction outcomes of the Hybrid (MobileNet + SelfAdaptiveConv2D) model that performs multiclass brain tumor classification. The model successfully detects "glioma_tumor" and "meningioma_tumor" and "pituitary_tumor" in brain MRIs corresponding to their authentic labels. The model correctly identifies standard brain imaging as "no_tumor." The model demonstrates exceptional capability to differentiate between tumor arrays and normal tissue classifications using MRI scans according to the research results.

Conclusion

In conclusion the research introduces a Self-Adaptive deep learning model which combines MobileNet and a SelfAdaptiveConv2D layer to improve brain tumor classification of noisy MRI images. The dynamic parameter adjustment mechanism of the model allows it to enhance its feature extraction performance and classification accuracy by surpassing conventional deep learning approaches at a 95% accuracy level. Advanced preprocessing methods such as grayscale conversion combined with CLAHE-based contrast enhancement along with Gaussian blur noise reduction and normalization buildup the system's resilience. The fuzzy border transformation applied to the ImageDataGenerator enhances generalization ability which leads to better performance when working with different types of datasets. Multiple accuracy tests and precision calculations together with F1-score value assessments and sensitivity measurements and specificity tests along with confusion matrix analysis demonstrate the model's worthwhile stability for medical image categorization purposes. Future developments will concentrate on applying the model to 3D MRI scans along with multi-modal imaging while working on real-time hospital implementation of privacy-protected federated learning for automated tumor identification and localization and explanations for AI interpretation and inclusion of IoMT for ongoing patient tracking. The further development of this model will increase its accuracy rate and implementation robustness to make it a vital clinic-based tool for early precise brain tumor diagnosis.

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Conflict of Interest Statement

Authors declare that there is no conflict of interest for publication of this work.

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