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DEEP NEURAL NETWORK FOR ENHANCEMENT OF ACCURATE BRAIN TUMOR DETECTION IN MEDICAL IMAGING

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Abstract

This research paper proposed a framework designed to enhance the accuracy of brain tumor (BT) detection through the integration of deep learning (DL) and machine learning (ML) methodologies. The model implemented on publicly available MRI image dataset of brain tumors collected from the Kaggle repository. Histogram equalization is applied on the dataset to enhance the contrast features of the MRI images. These pre-processed images are then used to extract features from the images using transfer learning models such as MobileNetV3 and ResNet50. These extracted feature vectors then fed into the traditional machine learning model such as Logistic Regression (LR), Support Vector Machine (SVM), Random Forest (RF), K-Nearest Neighbors (KNN), and XGBoost for classification. The ResNet50 model paired with Logistic Regression achieving a peak classification accuracy of 95% alongside superior scores in precision, recall, and F1-measure. ResNet50 derived features consistently yielded the highest accuracy for ensemble methods like Random Forest and XGBoost. Features extracted by the lightweight MobileNet architecture were more compatible with SVM and KNN algorithms. These findings validate the proposition that hybrid architectures which leverage the feature extraction process of deep learning combined with the computational efficiency of machine learning classifiers can substantially improve the performance and accuracy of brain tumor diagnostic systems.

Keywords: Machine learning (ML), Deep Learning (DL), Logistic Regression (LR), Support Vector Machine (SVM), Random Forest (RF), K-Nearest Neighbors (KNN).

1. Introduction

Brain tumors (BT) are characterized by the pathological and uncontrolled division of cells within the brain constituting a critical health challenge associated with significant morbidity and mortality across all age group. The broad histological classification of these neoplasms divides them into benign tumors which are typically slow-growing, non-cancerous, and remain localized and malignant tumors which are cancerous exhibit aggressive growth and have the potential to invade surrounding tissues or metastasize. BT are further defined by their origin: primary tumors, such as gliomas arise from brain tissue itself whereas secondary tumors are metastatic lesions that originate from cancers elsewhere in the body and spread to the central nervous system (CNS). The clinical presentation of a BT is profoundly influenced by its size histological type and precise intracranial location often manifesting through symptoms such as persistent headaches, seizures, cognitive deficits, and alterations in personality. Diagnosis has historically been dependent on the subjective interpretation of neuroimaging particularly magnetic resonance imaging (MRI) by specialized clinicians. However, the emerging integration of artificial intelligence (AI), ML and DL algorithms is revolutionizing neuro-oncology by providing tools for automated, objective and highly accurate tumor detection and classification. This result into augmenting diagnostic precision and supporting clinical decision making.

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This research proposes a two-stage hybrid methodology for the automated detection of BT in medical images. In the first stage high-level discriminative features are extracted from input imagery using pre-trained DL model namely MobileNetV3 and ResNet50. In the second stage these extracted feature vectors serve as input to a suite of conventional ML classifier such as LR, SVM, RF, KNN and XGBoost to perform the final binary or multi-class classification.

The objective of this research paper is

- To develop predictive system for identifying brain tumor by integrating ML algorithms with DL driven feature extraction from MRI images.
- To employs transfer learning utilizing pre-trained models including MobileNetV3 and ResNet50 to extract critical features from brain MRI images.
- To evaluate and compare the performance of multiple ML classifiers including LR, SVM, RF, KNN, and XGBoost on the extracted deep features.
- To conduct a thorough evaluation of all model configurations using standard performance metrics of accuracy, precision, recall, and the F1-score.

The paper aims to evaluate the performance of machine learning model. The key contribution of this paper include:

Image enhancement: in this paper we perform image contrast enhancement using histogram equalization by redistributing pixel intensities. It helps in highlighting important features like tumors in MRI scans before passing them to the model.

Model Development: In this paper we use transfer learning model for the feature extraction and then apply ML model for the classification of the images

In this section we discussed the introduction of the paper. In the second section we will discuss literature survey. In the third section we will discuss methods and material and in the last section we will discuss about result and discussion of the paper.

2. Literature Survey

Wankhede and colleagues utilized MRI images for glioblastoma grade prediction. The methodology involved several stages: First, the collected MRI data was pre-processed by normalizing intensity values based on the brain region's mean and standard deviation. Subsequently, noise was reduced using a bilateral filter. The tumor was then segmented automatically via a Modified Fuzzy C-Means Clustering (MFCM) algorithm. Following feature extraction, a Multilevel Layer Convolutional Neural Network (MLL-CNN), built upon the Faster R-CNN framework, was implemented for classification into high-grade and low-grade tumors (1). In their study Sandeep Kumar Mathivanan and colleagues applied DL architectures such as ResNet152, VGG19, DenseNet169, and MobileNetV3 to classify brain tumors from MRI images. They used five-fold cross validation and image enhancement technique for the MRI images. The MobileNetv3 is achieved highest accuracy with 99.75%. But this not demonstrate the generalization across diverse dataset (2). Baiju BabuVimala and others focuses on classification of Brain tumor using MRI images. They used MRI figshare dataset for train and evaluate the model. They used transfer learning model like efficientnet. They implement the data augmentation technique to enhance model effectiveness. EfficientNetB2 achieved highest accuracy of 99.06%, precision 98.73%, recall 99.13%, and F1-score 98.79% (3). Ramtekkar and colleagues demonstrated a high-accuracy approach to brain tumor detection by integrating advanced optimization techniques with a Convolutional Neural Network (CNN). Their system pre-processed MRI data with Gaussian, mean, and median filters, followed by feature extraction using GLCM. The feature selection phase was significantly enhanced by leveraging a suite of metaheuristic algorithms (Ant Colony, Gray Wolf and Whale Optimization). This comprehensive methodology culminated in a classification accuracy of 98.9% using the optimized CNN (4).

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Novsheena Rasool and others perform the comparative analysis for the brain tumor detection using ML and DL techniques. They implemented DL models such as CNN, VGG16, ResNet50, and hybrid models. They used publicly available dataset such as BraTS and Figshare for train the models. In the initial stage they performed image pre-processing and augmentation. The hybrid DL model achieved highest accuracy of 95%. This DL model has a capacity to capture spatial and textural MRI features, reducing diagnostic delays and enhancing clinical decision-making (6). Bhagyalaxmi et al. conducted a comparative analysis of feature extraction methods with and without optimization techniques for medical image classification. Their approach involved extracting features using a hybrid CNN model, which were then classified using a SVM and an ensemble learning method. Furthermore, the authors implemented segmentation architectures utilizing Mask R-CNN with backbones such as DenseNet-41 and GoogleNet (7). P. K. Ramtekkar and others introduces optimized techniques for the accurate brain tumor detection. They apply compound filter by combining gaussian, mean and median filter for enhance the image quality. They used GLCM techniques for the feature extraction from the imags. They implemented CNN classification model with accuracy of 98.9% (8). Kamini Lamba and others used publicly available MRI dataset for train the model. They performed data augmentation technique for standardize and expand the dataset, followed by transfer learning using a VGG-16 architecture to extract deep spatial features. To enhance the classification performance they used linear SVM. The experimental result shows that with VGG16 architecture they get 98.87% for accuracy, 99.09% for precision, 98.73% for recall, 99.02% for specificity, and 98.91% for F1-score (10). Monika Agarwal and others implemented hybrid model for the early detection of brain tumor. For improve low contrast MRI images they performed Optimized Discrete-Time Wavelet-based Contrast Histogram Equalization (ODTWCHE). After contrast enhancement they implemented transfer learning inception v3 model for tumor classification. The proposed methodology achieved accuracy of 98.89% (12). The author implemented model operates in two stages. The first differentiates between neoplastic and non-neoplastic brains, while the second classifies the tumor types. The study evaluated four optimizers such as Adam, Nesterov Momentum, RMSProp, and Adagrad for this task. Adam optimizer yielded the highest performance in the first stage of tumor detection achieving 100% training accuracy alongside 98% validation and test accuracy. For the subsequent tumor type classification Nesterov Momentum was most effective attaining 100% training accuracy and 92% validation and testing accuracy (13).Tripty Singh and others introduces BrainNet architecture for accurate classification of the brain tumor MRI images. They used this novel CNN model to address the challenges posed by irregular tumor shapes and the scarcity of expert radiologists in developing regions. BrainNet model is compared with several transfer learning models including VGG13, VGG16, VGG19, InceptionResV2, and SqueezeNet. The BrainNet achieved precision of 94.75%, training accuracy of 99.96%, and testing accuracy of 97.71% (14). T. Lakshmi Prasanthi and others conduct the comparative analysis of advanced DL model such as DenseNet121, EfficientNetB7, InceptionResNetV2, InceptionV3, ResNet50V2, VGG16, VGG19 for classification of MRI images. They implemented hybrid CNN model with precision of 96.63%. Results indicate VGG19 and InceptionResNetV2 show effectiveness in detecting glioma tumors. The proposed hybrid model demonstrates higher performance and reliability, emphasizing the potential of integrating multiple deep learning frameworks for more accurate and timely brain tumor detection (15). The authors proposed a hybrid DL model that integrates an AlexNet architecture with a GRU network for the multiclass classification of brain tumors from MRI data. Their methodology involved pre-processing images with a non-local means filter. In this model AlexNet extracts spatial features through its convolutional layers while the GRU component captures sequential dependencies and addresses the gradient vanishing problem. Hyperparameter tuning was employed to enhance generalization and prevent overfitting. The proposed hybrid model achieved an accuracy of 97%, a precision of 97.63%, a recall of 96.78%, and an F1-score of 97.25% (16). Shyo Prakash Jakhar and others proposes DL based segmentation technique for BT detection using MFFN. In this proposed methodology they used pixel level segmentation combined with fractal residual learning and multi-scale feature extraction to enhance sensitivity and accuracy. Multi-level segmentation helps preserve tumor information while minimizing false regions so it improves accuracy of the models. Experimental results showed a segmentation accuracy of 94.66%, sensitivity of 94.42%, and specificity of 92.81% (18).

Kavita A and others introduces brain tumor detection technique that combine digital twins, IoT-based cloud storage, and advanced ML techniques. This digital twins enable device is capture MRI images and stored this images centrally using IoT systems. The feature selection is performed using PSO. The extracted feature are classified using CNN, SVM and Extreme Learning Machines (ELM). The study highlights the efficiency of CNN in detecting abnormal tissues within MRI scans (19). The authors developed 13-layer 2D CNN, 9-layer 2D CNN, and a CNN-LSTM model. The MRI medical images used to train these models. Comparative analysis shows that the ensemble approach performs better than the individual models (20). Rita Appiah and others addresses the need for efficient BT detection by comparing a low-order model POD integrated with a CNN, against standard deep learning models. The methodologies implement POD-CNN to reduce computational complexity while retaining predictive power. The proposed model achieved 95.88% accuracy with one-third the computational time as compared with CNN (21).

3. Methods and Materials

For this study on BT prediction from MRI images using DL, a comprehensive dataset comprising both healthy and diseased MRI images were collected form online kaggle repository. A total 7000 MRI images we divided in to the train and test folder. The dataset employed in this study was divided into two subsets with 80% used for training the model and 20% reserved for performance evaluation. It consists of medical images classified into four categories such as glioma, meningioma, pituitary tumor and no tumor. These represent common types of brain tumors. Gliomas specifically are tumors that originate in the brain's glial cells. Pituitary class contains images of tumors located in the pituitary gland which can affect hormonal functions. The no tumor class serves as the control group comprising images from individuals with no detected abnormalities. This dataset is used for multi class classification and it is suitable for train the model using transfer learning models.

3.1 Flow of algorithm

A. Image Contrast Enhancement

In the first stage, contrast enhancement is applied to improve the visual quality of MRI images and emphasize diagnostically relevant structures. Let an input MRI image be denoted as $I \in \mathbb{R}^{H \times W}$. Histogram equalization is employed to redistribute the pixel intensity values uniformly, resulting in an enhanced image expressed as:

$$I_{he} = \text{HistogramEqualize}(I)$$

This transformation improves feature visibility and supports effective representation learning in subsequent stages.

B. Feature Extraction Using Transfer Learning

In the second stage, deep extraction is performed using pre-trained transfer learning models, namely ResNet50 and MobileNet-V3. These networks are utilized as fixed feature extractors to obtain high-level representations from enhanced MRI images. The extracted feature vectors are defined as:

$$X_r = F_{\text{ResNet50}}(I_{he}) \in \mathbb{R}^d, X_m = F_{\text{MobileNet}}(I_{he}) \in \mathbb{R}^d$$

The final feature vector is generated through feature fusion via concatenation:

$$X = [X_r; X_m] \in \mathbb{R}^{2d}$$

This fused representation captures complementary information from both deep architectures.

C. Classification Using Machine Learning Models

In the third stage, the fused feature vector $X$is supplied to multiple machine learning classifiers for training and prediction. The classifiers considered include Logistic Regression (LR), Support Vector Machine (SVM), Random Forest (RF), K-Nearest Neighbors (KNN), and XGBoost. These models are trained to learn discriminative patterns for accurate MRI image classification.

D. Performance Evaluation

In the final stage, the trained models are evaluated using standard performance metrics. Classification effectiveness is assessed in terms of accuracy, precision, recall, and F1-score, providing a comprehensive evaluation of the proposed framework.

3.2 Histogram equalization

Step 1: Image Intensity Analysis

The MRI images are grayscale images in which each pixel is represented by a single intensity value ranging from 0 to 255. Let the input image be denoted as $I(x,y)$of size $M \times N$, where $x$and $y$represent the spatial coordinates.

Step 2: Histogram Computation

In this step, the frequency of occurrence of each gray-level intensity is computed. Let $r_k$denote the k-th gray level and $n_k$represent the number of pixels with intensity r_k. The normalized histogram is calculated as:

$$P(r_k) = \frac{n_k}{M \times N}, k = 0,1, \dots, L-1$$

where $P(r_k)$represents the probability of occurrence of the gray level r_k, and Ldenotes the total number of gray levels.

Step 3: Cumulative Distribution Function (CDF) Calculation

The cumulative distribution function (CDF) is computed as the cumulative sum of the normalized histogram:

$$C(r_k) = \sum_{j=0}^{k} P(r_j)$$

The CDF represents the accumulation of pixel intensities across the gray-level range and is used to redistribute intensity values more uniformly over the entire range $[0, 255]$. This redistribution enhances the overall contrast of the image.

Step 4: Intensity Mapping

Using the computed CDF, the original gray-level intensities are mapped to new intensity values according to:

$$S_k = \text{round}((L-1) \times C(r_k))$$

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This transformation redistributes pixel intensities based on their cumulative probabilities, resulting in a flatter and more uniform histogram.

Step 5: Image Transformation

In the final step, the transformation function is applied to all pixels in the original image. Each pixel intensity r_k is replaced with its corresponding mapped value S_k, producing the histogram-equalized image:

$$I_{eq}(x,y) = T(I(x,y))$$

This operation generates the contrast-enhanced output image, where each pixel value reflects its position within the cumulative intensity distribution.

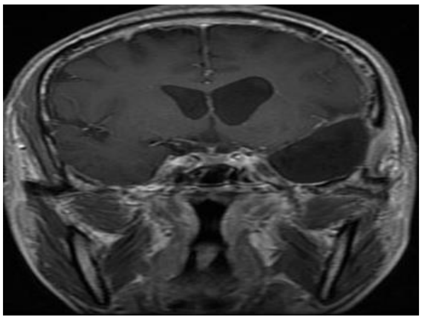

Figure 1: original Image

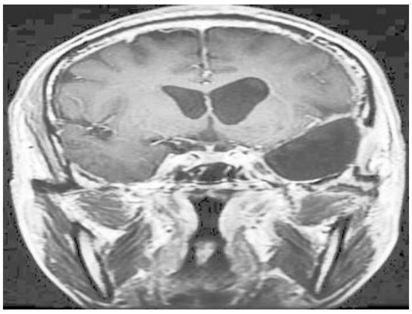

Figure 2: Histogram equalized image

The above figure 1 demonstrates original grayscale MRI brain image. Figure 2 shows MRI image after applying histogram equalization to the original image. Histogram equalization enhances the overall contrast of an image by adjusting and redistributing its intensity levels. In the original image darker and brighter regions are not distinctly visible due to the limited intensity range. The histogram equalization process enhances these hidden features by spreading out the most frequent intensity values across the entire range of pixel values between 0 to 255. This result shows brain tissues and tumor regions are more visible and distinguishable. Figure 2 shows improved brightness and better contrast so that making image is more visible for analysis. This preprocessing step is particularly useful in medical imaging tasks to enhance features for ML and DL applications.

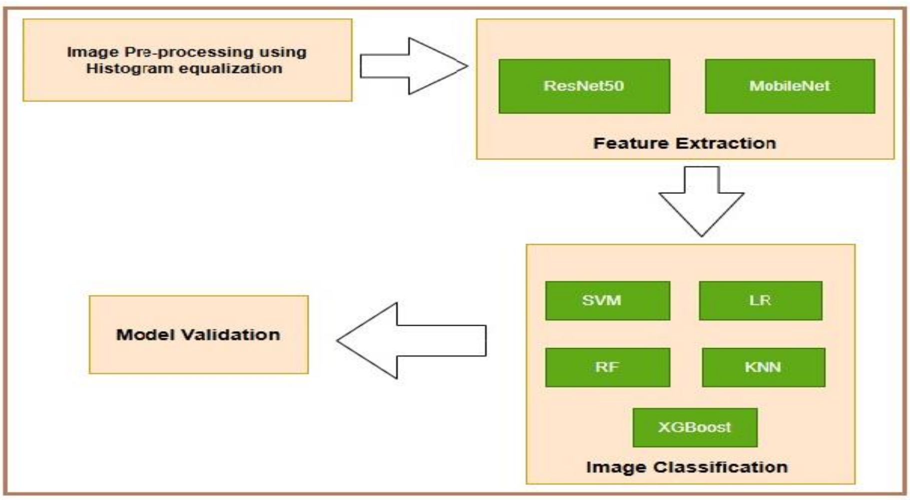

Figure 3: Proposed Methodology

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Figure 3 illustrates the proposed methodology for the BT classification pipeline which consists of image preprocessing, feature extraction, classification, and model validation. In the initial step raw MRI scans are processed using histogram equalization to enhance contrast and highlight tumor affected areas more clearly thereby facilitating more effective feature extraction.

In the next step transfer learning models such as ResNet50 and Mobilenet are applied to automatically extract discriminative features from the preprocessed images. These features then fed into the ML classification model such as LR, SVM, RF, KNN and XGBoost for the classification and distinguish between tumor types. The result of the classification evaluated using model validation metrics to assess the performance of each classifier.

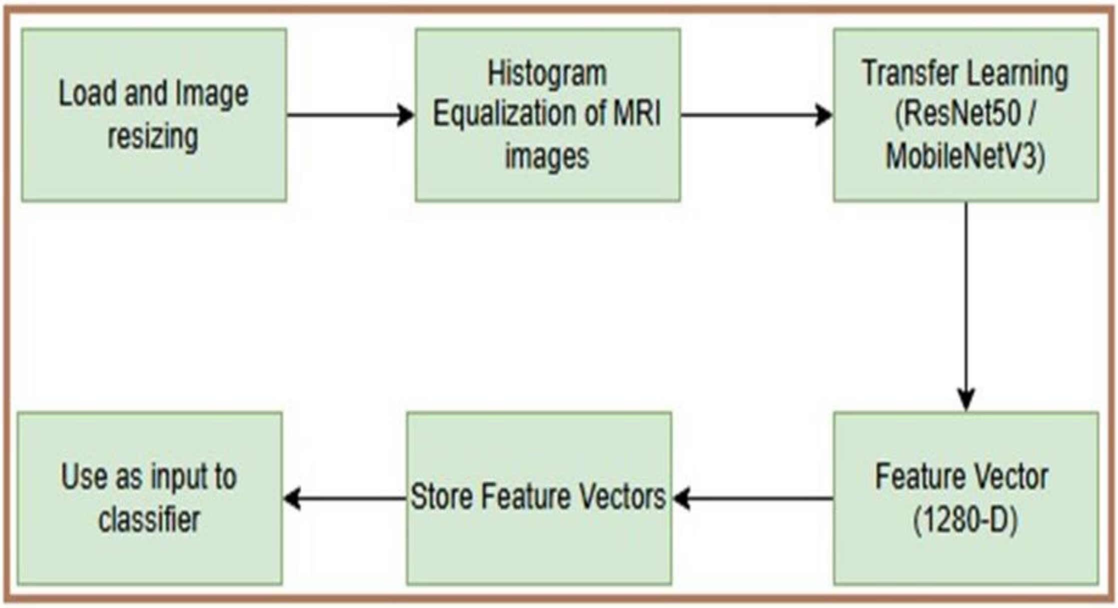

Figure 4: Feature extraction using transfer learning

Figure 4 illustrates the structured pipeline used for feature extraction and classification of brain MRI images. MRI scans are loaded and resized to a fixed dimension to ensure compatibility with deep learning models. In the next step apply histogram equalization for MRI images that enhances contrast and redistributing pixel intensities. After this step transfer learning is applied using pre-trained deep learning models such as ResNet50 and MobileNetV3.

These models extract deep features from the MRI images without requiring training from scratch. Feature vector encapsulates essential spatial and textural characteristics from the input image. In the last step this feature vector serves as input to ML classifiers for tumor classification. The proposed hybrid model establishes an efficient framework for medical image analysis and tumor detection by integrating three key components of image enhancement via histogram equalization, feature extraction using transfer learning, and classification with a ML model.

4. Result and Discussion

This chapter presents the study's results and provides a comparative analysis with existing systems. The research methodology employed a DL based transfer learning approach for feature extraction, followed by classification. All experiments were conducted using the Python programming language on the Google Colab platform utilizing a T4 GPU for accelerated processing.

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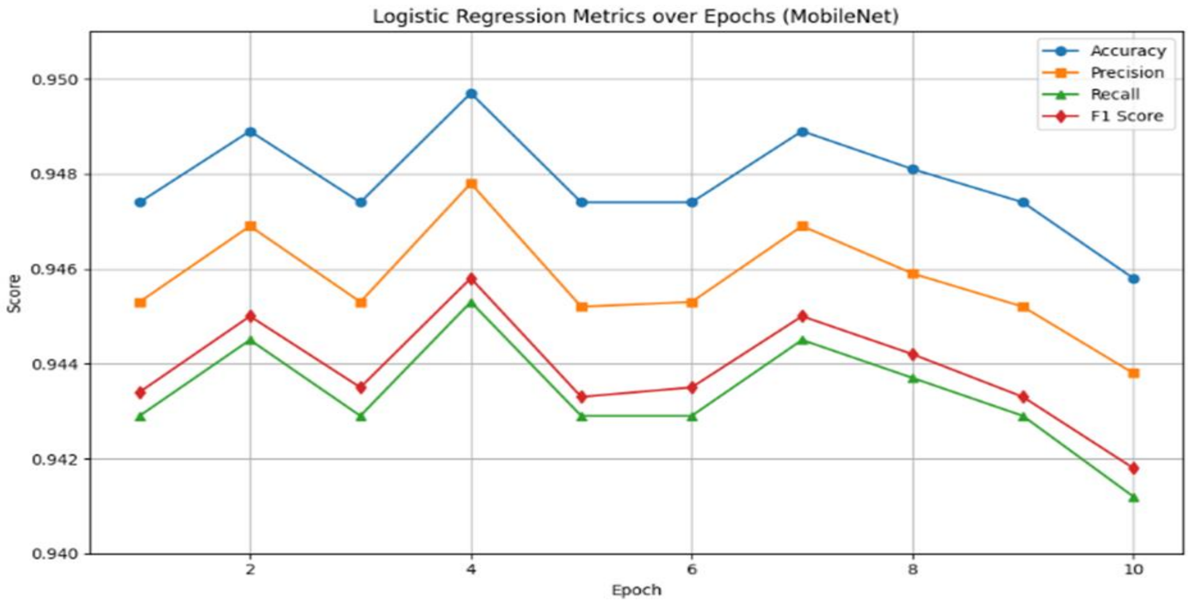

Figure 5: Logistic regression over epoch for MobileNetV3

Figure 5 illustrates the performance of the LR model utilizing MobileNetV3 features over ten training epochs. The results indicate high performance across all evaluation metrics of accuracy, precision, recall, and F1-score during training. A peak accuracy of 95% was achieved around the fourth epoch, demonstrating stable and reliable classification performance. Furthermore, precision and recall metrics followed a similar trend with minimal variation.

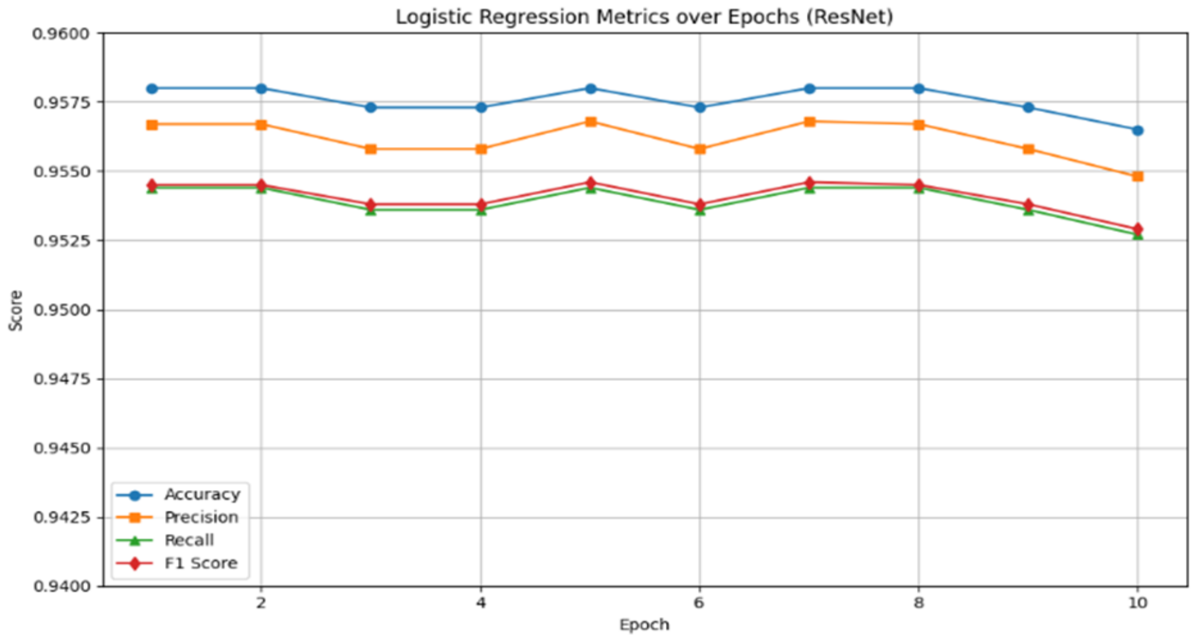

Figure 6: Logistic regression over epoch for ResNet50

Figure 6 illustrates the performance of the LR model utilizing features extracted from ResNet50 across ten training epochs. Model efficacy was evaluated using accuracy, precision, recall, and F1-score all of which indicate strong and reliable performance. An accuracy of 95% demonstrates highly reliable classification while similarly high precision and recall scores indicate a well-balanced model with robust sensitivity and specificity.

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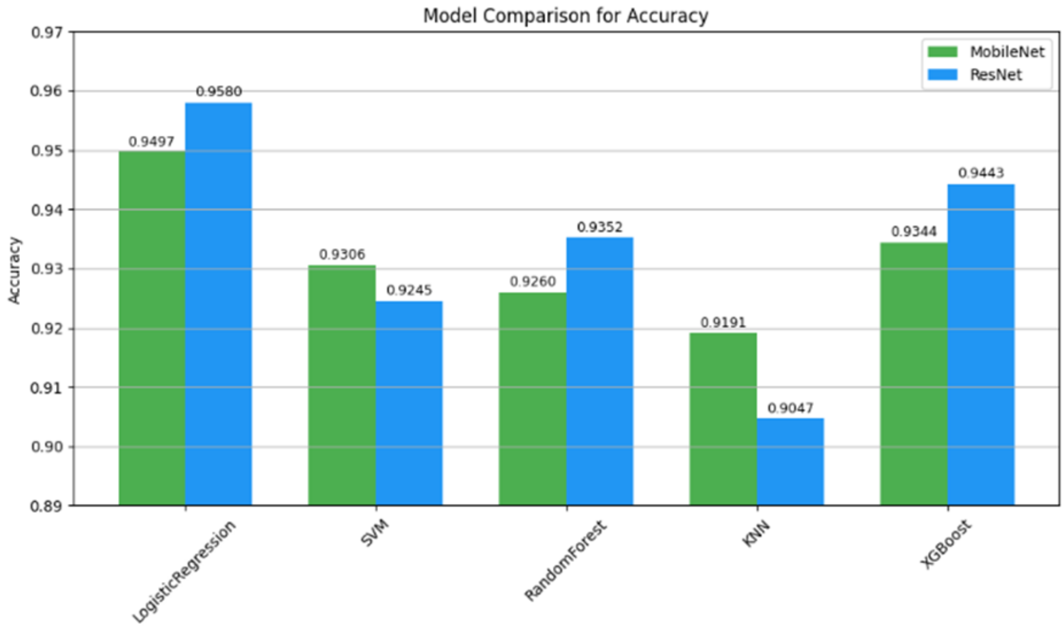

Figure 7: Model Comparison for accuracy

The above figure 7 demonstrates comparative analysis of classification of accuracy achieved using ResNet and MobileNet as feature extractor for ML algorithm like LR, SVM, RF, KNN and XGBoost.in above graph we take best accuracy across 10 epoches. As shown in the above figure LR with ResNet feature extractor get highest accuracy of 95%. The ResNet gives the best accuracy for LR, RF and XGBoost and MobineNet gives best accuracy for SVM and KNN. The above comparison shows that ResNet gives superior classification performance and better generalization combined with traditional ML algorithms.

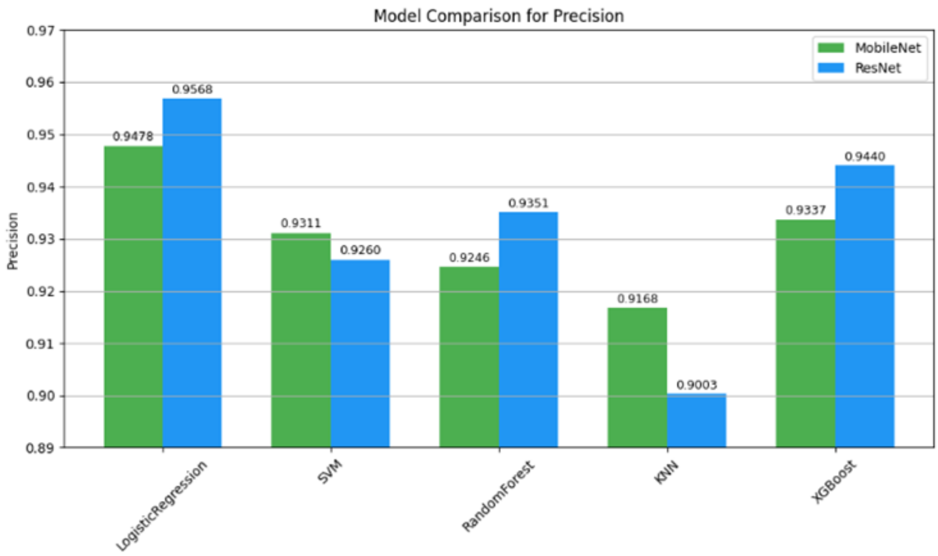

Figure 8: Model Comparison for precision

The above figure 8 demonstrates comparative analysis of classification using precision achieved using ResNet and MobileNet as feature extractor for ML algorithm like LR, SVM, RF, KNN and XGBoost. As shown in the above figure LR with ResNet feature extractor get highest accuracy of 95%. The ResNet gives the best accuracy for LR, RF and XGBoost and MobineNet gives best accuracy for

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SVM and KNN. The above comparison shows that ResNet gives superior classification performance and better generalization combined with traditional ML algorithms.

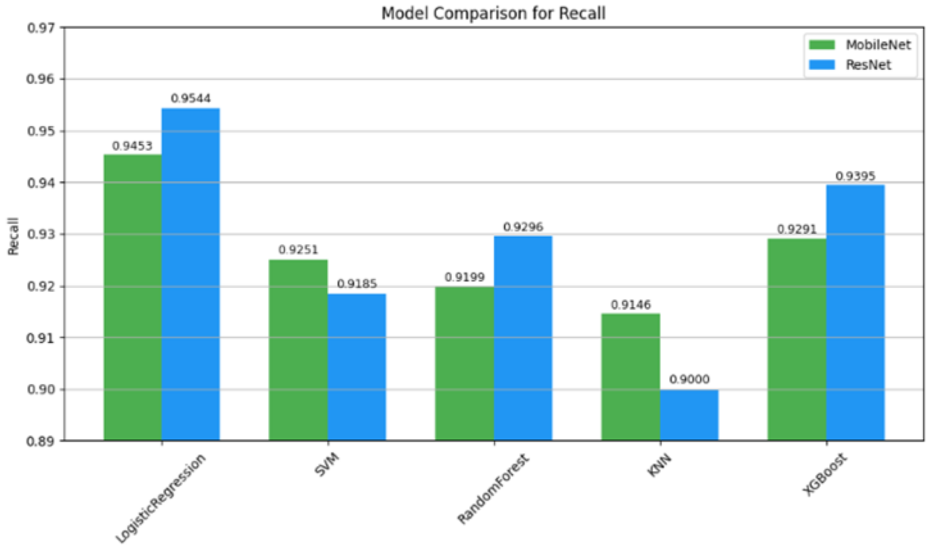

Figure 9: Model Comparison for recall

The above figure 9 demonstrates comparative analysis of classification using recall as evaluation metrics achieved using ResNet and MobileNet as feature extractor for ML algorithm like LR, SVM, RF, KNN and XGBoost. As shown in the above figure LR with ResNet feature extractor get highest accuracy of 95%. The ResNet gives the best accuracy for LR, RF and XGBoost and MobineNet gives best accuracy for SVM and KNN. The above comparison shows that ResNet gives superior classification performance and better generalization combined with traditional ML algorithms.

5. Discussion

The existing system focuses on the single transfer learning model or conventional deep learning algorithms [1-5]. The proposed system integrates the image contrast enhancement using histogram equalization with feature extraction using transfer learning model of ResNet and MobileNet and hybrid classification pipeline using ML models such as LR, SVM, RF, KNN and XGNoost. The existing system achieved high accuracy but lack in model generalization [6-14]. Our experimental result demonstrates that logistic regression with ResNet as feature extractor achieved peak accuracy of 95% with high precision and recall. In this proposed model use of histogram equalization enhances tumor visibility and segmentation quality.

Table 1 : Comparative analysis of proposed model with existing system

Authors and their work	Methodology used	Limitations
D. S. Wankhede et al. [1] implemented faster R-CNN model	They used Mean subtraction, bilateral filter for image pre-processing.	Lacks in transfer learning integration and Complex segmentation.
Baiju Babu Vimala et al. [3] perform data augmentation with EfficientNetB2 as feature extractor	They implemented CNN Deep learning model	Limited comparisons with DL model and single model usage

Praveen Ramtekkar et al. [4] uses optimized CNN for model building	They uses Gaussian, Mean, Median filters for image enhancement with GLCM and optimized feature selection	Complex optimization and limited transfer learning
Proposed System uses ResNet50 and mobilenetV3 as feature extractor and performs classification using ML techniques.	Uses histogram equalization for contrast enhancement and perform classification using LR, RF, SVM, KNN and XGBoost.	The proposed model does not includes dedicated **tumor segmentation step.** **The model is evaluated using single public dataset.**

6. Conclusion

This study validates the efficacy of a hybrid model that integrates DL based feature extraction with ML classification for brain tumor detection in MRI images. Features were extracted using pre-trained models such as ResNet50 and MobileNetV3 and subsequently classified using various ML algorithms. Experimental results demonstrated that LR utilizing ResNet50 features yielded optimal performance achieving 95% accuracy along with high precision, recall, and F1-score which indicates robust and balanced classification. Furthermore, ResNet50 features consistently produced superior results with RF and XGBoost classifiers whereas MobileNetV3 features proved more effective for LR and XGBoost models. Experimental results indicate that the Logistic Regression classifier performed effectively on features derived from both MobileNetV3 and ResNet50. These findings confirm that combining deep feature extractors with traditional ML classifiers significantly improves both the accuracy and generalization capability of brain tumor classification systems.

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