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A HYBRID DEEP LEARNING AND MACHINE LEARNING FRAMEWORK FOR EARLY ALZHEIMER'S DISEASE DETECTION FROM MRI

Swapnil P. Suryavanshi[1]*, Dr. Jitendra Saxena[2], Dr. Rajesh Nagar[3],

[1]Research Scholar, Department of CS&E, SAGE University, Indore, MP 452020, India
[2] Professor, Department of CS&E, SAGE University, Indore, MP 452020, India
[3]Associate Professor, SAGE University, Indore, MP 452020, India
Email: [1]mail4swapnil@gmail.com
[2,3]jsaxena531@gmail.com, errajesh973@gmail.com

Abstract: This research presents a hybrid approach based on deep learning (DL) and machine learning (ML) techniques for early detection of Alzheimer's disease (AD). The initial stages of AD can be difficult to discern as it courses through its progression. it is critical that an accurate and early detection of the disease occurs to facilitate appropriate intervention and treatment. An appropriate image analysis dataset is crucial, so the dataset utilized is from the Alzheimer's disease Neuroimaging Initiative (ADNI) which comprises magnetic resonance imaging (MRI) images for four classes: non-demented, very mild demented, mildly demented, and moderately demented. To improve the quality of the input images histogram equalization was employed to improve contrast and adjust for potential subtle structural details. Then features were extracted using transfer learning-based pre-trained Convolutional Neural Networks (CNNs) mainly MobileNetV3 and ResNet50 which are known for their speed, accuracy, and direct applicability to medical images. Features were extracted and were then used with a few traditional machine learning classifiers including Logistic Regression (LR), Support Vector Machine (SVM), Random Forest (RF), K-Nearest Neighbor (KNN), and XGBoost for classification. LR provided the best performance with an accuracy score of 99% for features extracted from ResNet50 and MobileNetV3. The proposed approach is less computationally expensive, and it reduces the complexity of the model. The result of this study is that a hybrid model that uses a transfer learning and a machine learning model provides a successful prediction of AD at an earlier stage of dementia.

Keywords: Machine learning (ML), Deep learning (DL), logistic regression (LR), Support vector machine (SVM), Random Forest (RF), K-Nearest Neighbor (KNN).

1. Introduction

Alzheimer's disease (AD) is the major brain disorder that affects the memory, behavior and mental process of the human being. AD is a type of dementia that affects the mental ability of humans. Mild Cognitive impairment (MCI) is early stage of AD. Mild dementia is the early stage of the MCI. In mild dementia humans forget recent events and repeat the questions. Also, humans face issues for solving the problems that indicate the cognitive decline. The next stage after mild dementia is moderate dementia. In moderate dementia the symptoms become worse. At this stage the damage in the brain spreads further leading to the more severe memory problem, communication problem and it leads to poor decision making in day-to-day life.

In the traditional method for predicting AD radiologist manually analyses MRI and PET images for detecting abnormality in the brain. The medical practitioners also consider memory-based tests, behavioral assessment test and cognitive scoring for identifying current stage of the AD. The DL model can automatically extract hierarchical features from MRI images and build ML models for the early identification of AD. This DL model that is trained on the large dataset can predict MCI at the early stage. This helps with proactive **intervention** before irreversible damage of the brain.

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In this research paper, we propose a hybrid model for early prediction of AD from medical images by combining transfer learning with machine learning techniques. Features are extracted from MRI images using transfer learning models such as MobileNetV3 and ResNet50 and these extracted features are used to build ML models such as LR, SVM, RF, KNN and XGBoost.

The objective of this research paper is

- To extract critical features from MRI images using pre-trained models such as MobileNetV3 and ResNet50.
- To integrate these extracted features with machine learning algorithms to develop predictive models for prediction of AD at early stage.
- To evaluate and compare the performance of multiple machine learning classifiers such as LR, SVM, RF, KNN, and XGBoost.
- To conduct a comprehensive performance analysis of each model combination using evaluation metrics such as accuracy, precision, recall, and F1-score.

The paper aims to evaluate the performance of machine learning models for early prediction of AD. The key contribution of this paper includes:

Image enhancement: A pre-processing methodology uses histogram equalization to augment the contrast of MRI images. This redistributes the intensity of the pixel enhancing critical features of the MRI images. These pathological features are indicative of the early stage of AD.

Model Development: A classification pipeline that utilizes a pre-trained CNN via transfer learning for automated feature extraction, upon which a machine learning classifier is trained to differentiate between various stages of cognitive impairment.

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

K.P. Muhammed and others perform comparative analysis of AD detection methods using ML techniques. They consider demographic data, MRI and PET images for the classification of the model. Combining imaging and clinical data with advanced ML models like SVM and CNN improves early AD prediction accuracy [1].Nilanjana Pradhan and others compares the effectiveness of structural MRI, EHR, and SNP data for detecting AD. They extracted the critical features from MRI images using deep learning models like Symmetrical Convolution Network (SCNN). For imaging dataset get 95.44 % accuracy and for HER dataset received 93.61% accuracy [2]. Rajasekhar Butta and others perform image preprocessing using histogram equalization, Gaussian filtering and skull stripping. they implemented segmentation on the images using U-Net optimized with Equestrian Ecosystem Optimization (EEO). They used hybrid HOA-AEO algorithm for the feature selection. The final ensemble model combines an Optimized ANN, Capsule CNN, and Autoencoder for classification. The result shows that proposed model better than traditional models [3]. Authors employs a dual method framework that combine bibliometric analysis with experimental validation to offer a holistic perspective on AD. Bibliometric assessment examines publication trends, key journals, and collaborative networks within the AD field using quantitative metrics. An experimental evaluation tests twenty classification models across two datasets, comparing their performance with and without feature selection. Seven feature selection methods are implemented to optimize model efficacy. Findings demonstrate that incorporating feature selection consistently improves diagnostic accuracy and computational efficiency [4]. A. M. Anusha Bamini and others uses MRI images for early detection of AD. They employed CNN, including ResNet50, ResNet101, ResNet50V2, ResNet101V2, InceptionV3 to classify AD stages. They performed data pre-processing and image augmentation to address overfitting problem [5].

Akhilesh Deep Arya and others used ADNI, OASIS and kaggle dataset for build the model. They perform the normalization, image augmentation and feature extraction on the image dataset. CNN models of ResNet, VGG and DenseNet achieved highest accuracy up to 99.4% and RNN achieves 91.2% of accuracy. The traditional machine learning algorithm like svm and random forest shows accuracy of 85.71% and 98% respectively. The multimodal approaches that combine MRI, PET and cognitive score enhance diagnostic accuracy [6]. Abebech Jenber Belay and others proposed a **quantum enhanced ensemble deep learning model** for AD classification using MRI scans. They merged ADNI-1 and ADNI-2 dataset from the kaggle repository to enhance sample diversity. They use adaptive median filter for noise filtering. Extracted features were classified using **Quantum Support Vector Machine (QSVM)** with a 5-qubit quantum feature map. They Apply CNN on OASIS dataset and get 99.68% accuracy, VGG16 on ADNI dataset and get 83.9% accuracy and apply AlexNet on ADNI dataset get 93.24% accuracy. The proposed **quantum-ensemble model** that ensambles VGG16, ResNet50 and QSVM achieved **99.89% accuracy [7]**. Louise Bloch and others uses the dataset such as ADNI, AIBL and OASIS to train the model and validation. They uses 3D MRI scan images for early detection of AD. They implemented 3D DenseNet, EfficientNet, SE-Networks deep learning models on ADNI dataset. Both ML and DL models perform similarly in categorization. The inferior and middle temporal gyri are the focus of the ML model. The left and right vessels, the entorhinal cortices, and the optical chiasm are the main targets of the DL model [8].

M. Menagadevi and others uses ADNI images for train the model. They implemented histogram equalization, intensity normalization and contrast stretching for image pre-processing. They used segmentation techniques to identify the region of interest from the brain images. Thresholding techniques, region based method, clustering and edge based methods are commonly used. In this paper authors make comprehensive analysis of different deep learning techniques and conclude that CNN shows success for segmentation of brain images [9]. Lovepreet singh Gill and others uses ADNI dataset for research. They perform feature extraction using GLCM and FOS. They divides the study in to four groups such as CN, AD, progressive MCI and static MCI. They used input feature combination of the GLCM and FOS. From this Random forest algorithm gives accuracy of 66.1 %, Decision tree gives 56.4% accuracy, SVM gives 59.2% accuracy [11]. Vasco Sa Diogo and others compares different ML models to diagnose AD an MCI using MRI images of the brain. They used ADNI and OASIS dataset to train the models. They evaluated multiple classifier and combine their results using voting systems. They used a mix of texture-based features (GLCM) and basic statistical features (FOS) as inputs. Among these, the Random Forest model performed best with 66.1% accuracy, followed by SVM gives accuracy of 59.2% and Decision Trees gives accuracy of 56.4%.[12]. Researchers created an advanced machine learning model to predict AD by combining different classification methods, including both linear and tree-based approaches. Hyun-Ji Shin and others analysed brain scans of dual-phase 18F-FBB imaging from 336 participants, categorized into three groups: 188 with Alzheimer's, 111 with MCI, and 37 healthy individuals. To distinguish AD patients from healthy controls, they tested multiple machine learning techniques such as RF and SVM. The RF model gives better accuracy than others ML algorithms [13]. Mingxia Liu and their research team developed an advanced deep learning system called DM2L that can simultaneously classify AD and predict clinical scores. Their approach combines MRI scan data with basic patient information like age, gender, and education level. They implemented specialized neural network architecture that perform multiple tasks at once for both disease classification and clinical score prediction. The researchers trained their model using two standard datasets such as ADNI1 and MIRIAD that contain brain scans and patient details [14]. Nianyin Zeng and others used data ADNI

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dataset which contains detailed brain scan and biomarker information. They removed the noise from the images, removing non-brain tissue, standardizing brain positioning, and separating different tissue types. They performed Principal Component Analysis (PCA) and reduce the features from 90 to 38 and keeping 95% of original information. They introduce smart feature selection method (MTFS) for choosing most relevant features from MRI images [15]. Haibing Guo and Yongjin Zhang conducted their study using the ADNI dataset. Their approach integrates multiple data sources such as genetic markers, clinical test results to better understand Alzheimer's disease and develop potential treatments.in their work they examines the ApoE E4 gene, which produces a protein crucial for normal brain function [16]. They specifically analysed resting-state fMRI data from ADNI dataset [17] to study this genetic connection. Their results showed that autoencoder models delivered the most accurate predictions among the methods tested [18].

3. Methods and Materials

For this study on Alzheimer disease prediction from MRI images using de7ep learning a total of 4000 MRI images from ADNI dataset used to extract the features from the images. These MRI images [19] are used to visualize brain structure and detect abnormalities. The non-demented images mean the patient has no dementia. The mild demented images show the early signs of dementia, but symptoms of AD are mild. MRI images of moderate demented show the patient dementia symptoms are more advanced affecting patient memory, thinking and daily activity. The very mild dementia means MRI images show the early sign of dementia before loss of memory.

3.1. Flow of algorithm

Algorithm 1: Proposed Processing Pipeline
Input: Labeled image dataset $D = \{(I_i, y_i)\}_{i=1}^{N}$, where $I_i \in \mathbb{R}^{H\times W}$and $y_i$is the class label
Output: Trained classifiers $\{\widehat{M}_j\}$and evaluation metrics on the test set
Step 1: Contrast Enhancement (Histogram Equalization)
for each image $I_i \in D$**do**
$I_i^{he} = \text{HistogramEqualize}(I_i)$

end for
Step 2: Deep Feature Extraction and Fusion
for each preprocessed image I_i^{he}**do**
1. Extract ResNet50 features:
$\mathbf{x}_{r,i} = F_{\text{ResNet50}}(I_i^{he}) \in \mathbb{R}^d$

2. Extract MobileNetV3 features:
$\mathbf{x}_{m,i} = F_{\text{MobileNetV3}}(I_i^{he}) \in \mathbb{R}^d$

3. Concatenate features to form the fused representation:
$\mathbf{x}_i = [\mathbf{x}_{r,i}; \mathbf{x}_{m,i}] \in \mathbb{R}^{2d}$

end for
Let $\mathbf{X} = [\mathbf{x}_1, \mathbf{x}_2, \ldots, \mathbf{x}_N]^T$denote the fused feature matrix.
Step 3: Model Training
Split $(\mathbf{X}, \mathbf{y})$into training and test sets: $(\mathbf{X}_{\text{train}}, \mathbf{y}_{\text{train}})$and $(\mathbf{X}_{\text{test}}, \mathbf{y}_{\text{test}})$.
for each classifier $M_j \in$ {LR,SVM,RF,KNN,XGBoost}**do**
Train the model using the training set:
$\widehat{M}_j \leftarrow \text{Train}(M_j, \mathbf{X}_{\text{train}}, \mathbf{y}_{\text{train}})$

end for

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Step 4: Model Evaluation

for each trained model $\widehat{M}_j$ **do**

1. Predict labels:
   $\hat{\mathbf{y}}_j = \widehat{M}_j(\mathbf{X}_{\text{test}})$
2. Compute evaluation metrics: **Accuracy**, **Precision**, **Recall**, and **F1-score**.

end for

3.2. Histogram Equalization

This study uses MRI images to train the model. Some of the MRI images did not have enough contrast in the dataset. We want to increase the quality for better feature enhancement. To improve the quality of the images we will use histogram equalization. We will now explain the process we took to complete histogram equalization on the original dataset.

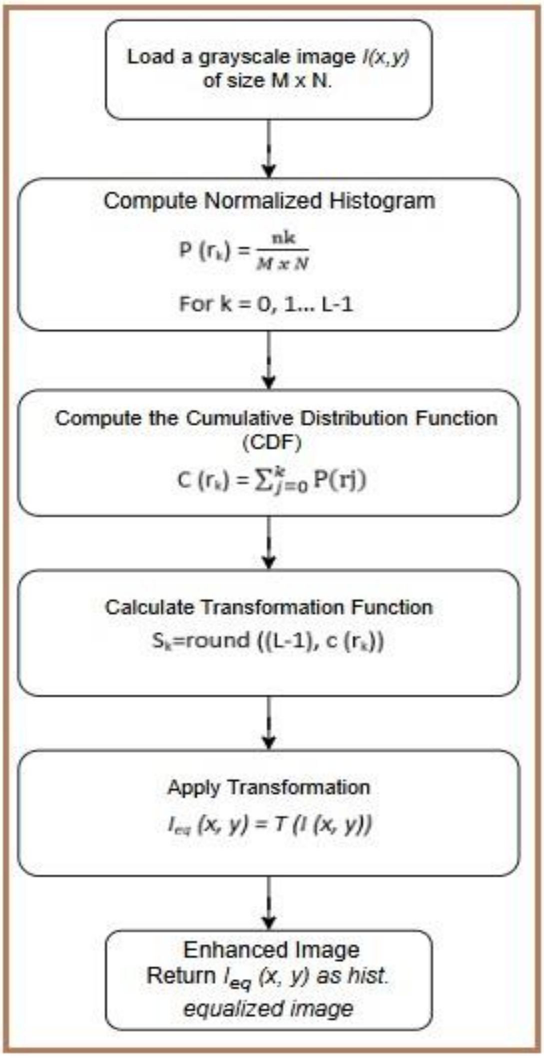

Figure 1: Flowchart of Histogram Equalization

The above figure 1 demonstrate the flowchart of image histogram equalization technique used for contrast enhancement. In the initial sep we need to analyse and adjust the pixel intensity value of the image. The MRI images are grayscale images and each pixel has a single intensity value between 0 to

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255. Load a grayscale image *I(x,y)* of size M x N. In the second stage as shown in above flowchart we count the how many times each intensity value between 0 to 255 appears. For this we use following:

$$P(r_k) = \frac{nk}{M\,x\,N}$$

For k = 0, 1,…., L-1

Where $P(r_k)$ is the probability of gray level r_k

In the next step we compute the cumulative distribution function (CDF). In this step compute the cumulative sum of normalized histogram.

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

The CDF shows that how pixel intensities accumulate across the range. It redistributes the pixel values to spread them more evenly across the entire range (0 to 255). This helps to enhance the contrast of the images. In the next step Use the CDF to map original intensities to new intensity.

$$S_k = \text{round}\,((L-1),c\,(r_k)\,)$$

Where L is the total number of gray levels

This ensures that redistributes pixel intensities based on their cumulative probability. This will make histogram flatter and more uniform. In the next step of histogram, equalization apply transformation to all pixels. In this step replace every pixel intensity r_k in the original image with its corresponding S_k from the transformation function.

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

This step gives the final output image. Every pixel gets a new value that corresponds to its position in the histogram's cumulative distribution.

3.3. Proposed Methodology

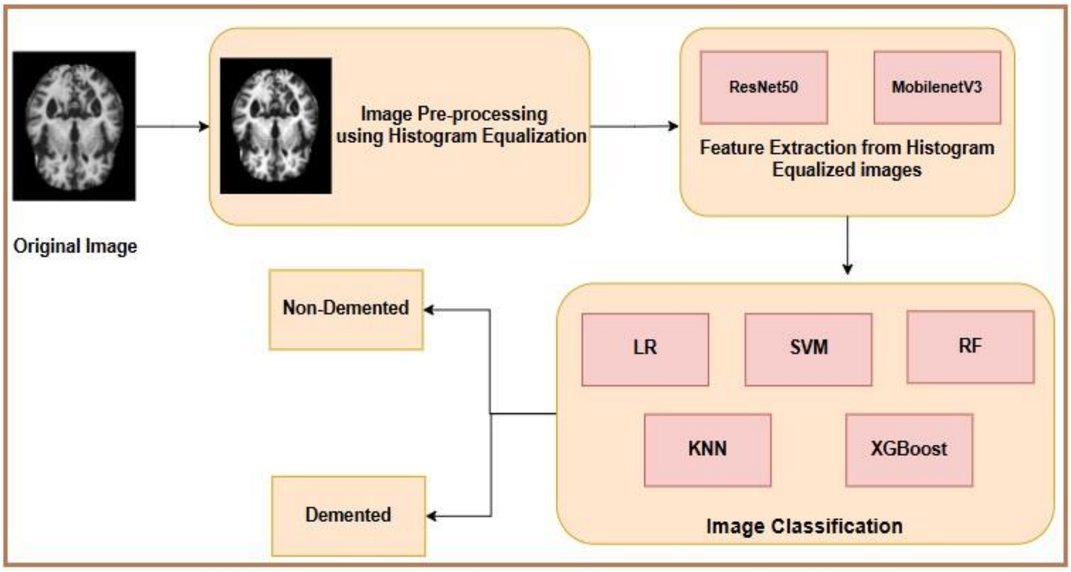

Figure 2: Proposed Methodology

The above figure 2 demonstrates the proposed methodology for the AD prediction. In the proposed methodology the original medical MRI images undergo for the image pre-processing using histogram

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equalization. The newly created dataset using histogram equalization used for extracting the features from the images. The features from the images were extracted using transfer learning techniques such as ResNet50 and MobileNetV3. These extracted features then fed into the machine learning classification model such as LR, SVM, RF, KNN and XGBoost for the classification of th images whether image is demented or non-demented. The result of the classification is evaluated using model validation metrics to assess the performance of each classifier.

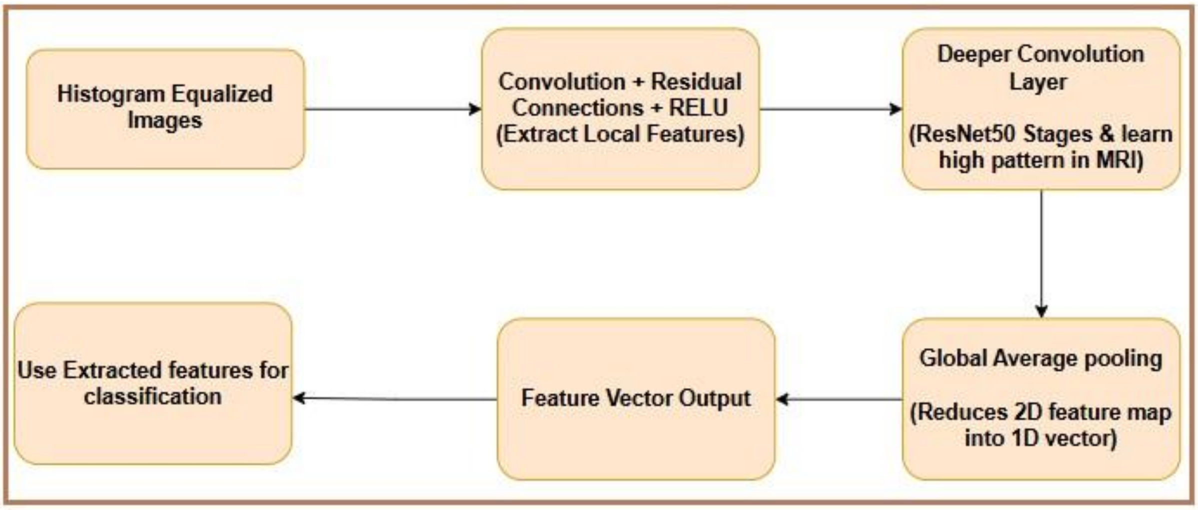

Figure 3: Feature extraction using ResNet50

The above figure 3 demonstrates the feature extraction methodology using ResNet50 transfer learning model. The processed images fed into the ResNet50 model and images go into convolution layers that capture both high level and low-level features. The low-level features include the texture and edges of the images and high-level features include brain structure and tissue degeneration features. After the global average pooling the final feature vector output is generated. These extracted features then used for the image classification.

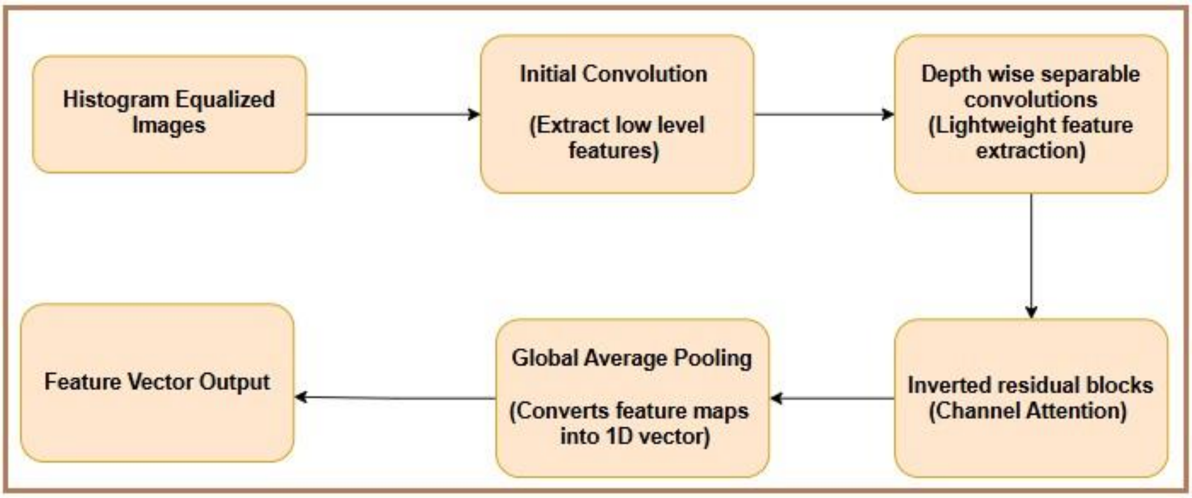

Figure 4: Feature extraction using MobileNetV3

The above figure 4 demonstrates the feature extraction methodology using MobileNetV3 transfer learning model. The mobilenetV3 is more efficient and lightweight for the feature extraction from medical images. The input MRI images pass through histogram equalization to enhance contrast and highlight important features. These images then passed through convolution layer for capturing low

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level spatial features such as edges and textures. In the next step these features passed to the depth wise separable convolutions that reduce computational complexity and preserving important information. This creates real time and low resource environment. In the next step use channel attention mechanism to focus on the most informative features and suppress the irrelevant features. In the next step global average pooling is applied that convert 2D feature map into 1D feature vector. This is used for the classification using machine learning techniques.

4. Result and Discussion

In this chapter we will talk about the results of our experimental study and give a complete comparison with existing systems. The main aim of this research was to test the effectiveness of the proposed deep learning framework with the accurate classification of medical images. In the proposed approach, we used transfer learning models such as ResNet50 and MobileNetV3 for the feature extraction and these features are fed into machine learning classifier for the final classification. The experiments were conducted using the Python programming language on the Google Colab platform with a T4 GPU. The overall objective of the research was to assess the effectiveness of the proposed framework.

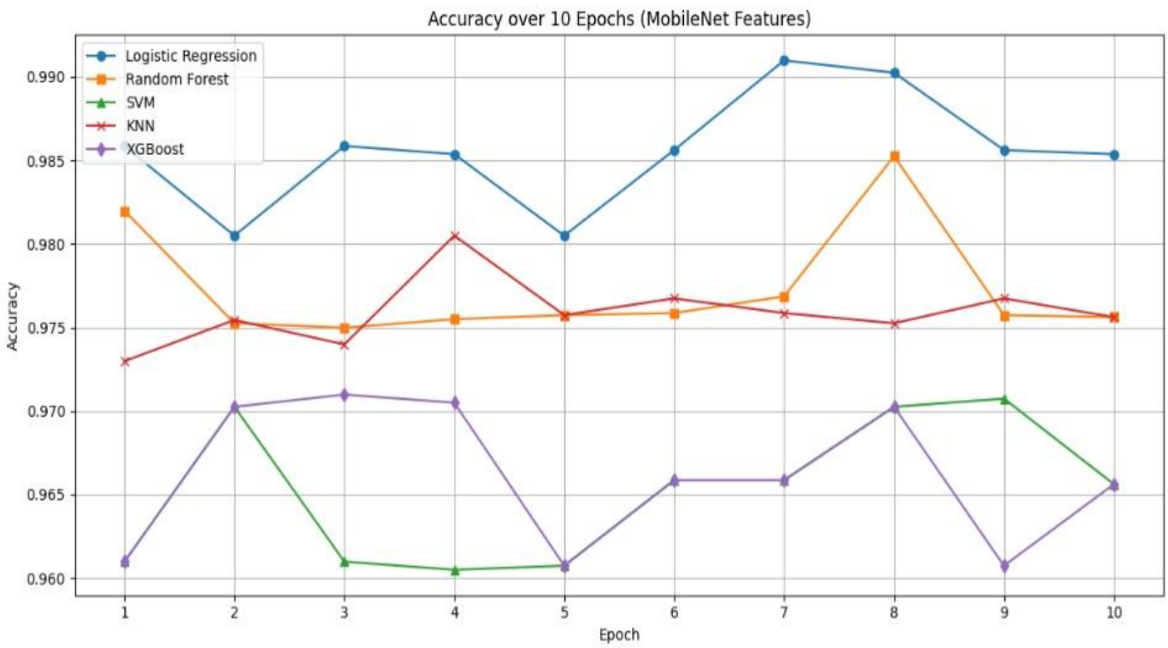

Figure 5: Result graph for accuracy over epoch for mobileNetV3 features

The above figure 5 demonstrates the result for the accuracy of over 10 epoches. The above figure shows classification accuracy for LR, RF, SVM, KNN and XGBoost machine learning models. These models were trained on features extracted using MobileNetV3 transfer learning model. This MobileNetV3 model is lightweight DL architecture for efficient feature extraction. The LR model shows the better performance among all ML models and achieves highest accuracy of nearly 99% at seventh epoch. The RF model shows stable accuracy with highest result at eight epoch and shows nearly 98% accuracy. The KNN model demonstrates moderate accuracy with nearly 97% of accuracy. The SVM and XGBoost both demonstrate moderate to lower accuracy as compared with other models.

Table 1: Classification evaluation using MobileNetV3 as feature extractor

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Classification Model	Accuracy (%)	Precision (%)	Recall (%)	F1 Score (%)
LR	99.09	98.15	92.10	95.15
SVM	97.02	96.85	93.25	94.87
KNN	98.04	98.13	94.92	92.85
RF	98.52	98.13	93.42	95.26
XGBoost	97.02	96.92	92.25	93.36

The above table 1 shows the performance comparison of five ML models using accuracy, precision, recall and f1score as evaluation metrics. The LR model achieved highest accuracy of 99% and shows strong compatibility with MobileNetV3 features. From all the above models RF shows the most balanced performance across all metrics with precision 98.13%, recall 93.42% and f1score of 95.26% accuracy. The SVM, KNN and XGBoost also show moderate performance. The LR model shows the more accurate result, but the random forest model shows the best balance between precision, recall and f1score.

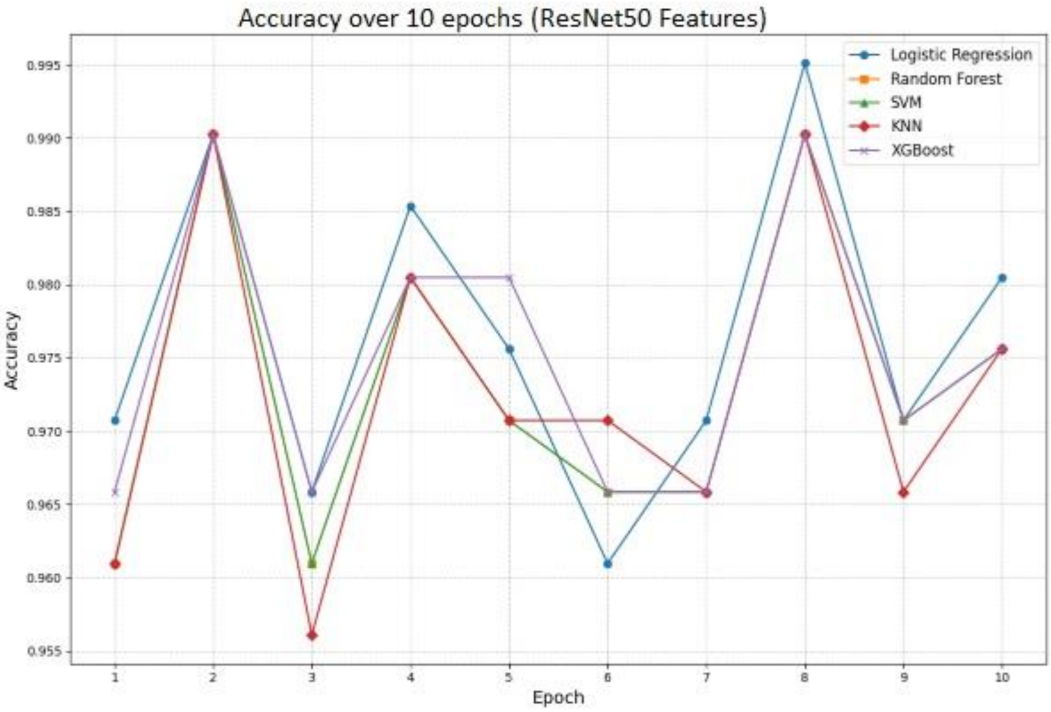

Figure 6: Result graph for accuracy over epoch for ResNet50 features

The above figure 6 demonstrates the result for the accuracy of over 10 epochs for the features extracted using ResNet50 transfer learning algorithm. The above figure shows the accuracy for the LR, SVM, RF, KNN and XGBoost machine learning classification models. All the ML models show higher accuracy above 95% that indicates that ResNet50 **features are highly discriminative** and effective for this dataset. The LR shows relatively stable and higher accuracy across the epoch compared with other models. The accuracy of the RF shows lower than the LR and it is less sensitive to the ResNet50 features. The SVM machine learning model also shows higher accuracy, but it is less stable compared with LR. The KNN model also shows higher accuracy of 99% at 8th epoch. The XGBoost models show less fluctuation than KNN and SVM that indicate the robust learning capability. The result graph from the above highlights that ResNet50 features enhance the classification performance across diverse ML models.

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Table 2: Classification evaluation using ResNet50 as feature extractor

Classification Model	Accuracy (%)	Precision (%)	Recall (%)	F1 Score (%)
LR	99.50	97.14	92.17	94.24
SVM	99.02	97.35	91.28	93.27
KNN	99.00	96.28	90.18	94.25
RF	98.09	98.27	91.22	94.29
XGBoost	99.01	97.13	90.87	95.13

The above table 2 shows the classification evaluation comparison for machine learning models. The LR achieved the highest accuracy with strong precision and recall that indicated balanced performance. From above results it indicates that all classifiers demonstrate high performance with accuracy above 98%.

5. Discussion

The existing system used traditional ML and DL techniques to train the models. In the proposed system we perform data pre-processing using contrast enhancement techniques such as histogram equalization. Extract the features using transfer learning techniques such as MobileNetv3 and ResNet50 and then perform the classification using machine learning techniques. The existing systems lack in the model generalization.

Table 3: Comparative analysis of proposed model with existing system

Authors and Methodology used	Limitations of existing models	Proposed System improvements
K.P. Muhammed et al. [1] implemented SVM, CNN with multimodal fusion	Get accuracy nearly 95% and require multimodal dataset that is less scalable	Achieved 99% accuracy and it is simpler and scalable.
Nilanjana Pradhan et al [2] uses MRI, EHR and SNP dataset and implemented SCNN Model with 95% accuracy.	This model used multiple heterogeneous data sources that were not available easily.	The proposed model avoid dependency on multiple data sources and used MRI images with 99% accuracy.
Rajasekhar Butta et al. [3] implemented U-Net with EEO Optimized. Create ensemble model using CNN, ANN and Autoencoder.	This model is complex hybrid model and required higher training time and computational overhead	Achieved higher accuracy with reduced complexity of the model by applying transfer learning for feature extraction.
A.M. Anusha Bamini et al. [5] implemented ResNet50 and inceptionV3 for multi stage AD classification.	Used traditional Deep learning models and require large dataset for training.	Combination of transfer learning with machine learning model for classification reduces overfitting and improves model generalization.
Vasco Sa Diogo and others [11] used GLCM & FOS features with ML model with accuracy of nearly 66%	Used features that have limited discriminative powers. This model shows limited accuracy	The proposed model gets higher accuracy.

6. Conclusion

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This paper demonstrates the effectiveness of a hybrid framework that combines ML and DL techniques for AD prediction. Features from the MRI dataset were extracted using transfer learning models such as ResNet50 and MobileNetV3, followed by classification with various machine learning algorithms. Histogram equalization was applied to enhance image contrast for improved feature extraction. The experimental results show that MobileNetV3 features with LR achieved the highest accuracy of nearly 99%, along with excellent precision, recall, and F1-score. KNN and XGBoost yielded moderate performance with MobileNetV3 features. ResNet50 features with LR achieved the highest accuracy of 99.5%, demonstrating robust precision, recall, and F1-score. SVM and RF were less sensitive to ResNet50 features compared to LR. The results indicate that the LR model combined with features extracted from ResNet50 and MobileNetV3 show excellent classification performance. This research highlights that integrating DL based feature extraction with ML based classification significantly enhances the accuracy of AD prediction.

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