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RESEARCH ARTICLE OPEN ACCESS

EARLY ALZHEIMER'S DISEASE DETECTION BY USING RESNET FOR EXTRACTION OF FEATURES WITH SVM TUNING FOR CLASSIFICATION

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ABSTRACT

Early detection of Alzheimer's disease (AD) is vital for effective intervention and management. This study introduces a novel approach that employs a ResNet architecture for feature extraction from neuroimaging data, coupled with Support Vector Machine (SVM) tuning for classification. We utilized a dataset of MRI scans from subjects at various stages of cognitive decline. The ResNet model was fine-tuned to identify complex patterns in brain structure indicative of early AD. Features extracted from the network's final layers were then input into an SVM classifier, optimized through grid search to improve classification accuracy. The parameters are tuned and the final layer in Resnet-53 is used for Support Vector Machine (SVM) model. It is mainly used for detection of Alzheimer's, and it addresses the both binary and multiclass classification. But we are using multiclass labels are used so it is used for multiclass classifications. Bayesian optimization with Hyperopt is used in a fine tune process to find the hyperparametrs space, optimizing key variables such as kernel selection and regularization to increase the performance of the model on the validation set. The proposed method is used to show the most accurate difference between normal cognitive aging and Alzheimer's disease, which is so sensitive and specific to achieve. Multimodal data is combined to increase the models performance and provides comprehensive tools for early detection.

I. INTRODUCTION

Alzheimer's disease (AD) is a increasing neurodegenerative condition described by intellectual regression, memory loss, and weakened decision-making. It is one of the heading causes of dementia, involving millions of people worldwide [1]. The prompt and correct diagnosis is important for appropriate interference and advanced patient outcomes. However, the conventional diagnostic methods, involving clinical assessments and neuropsychological tests, are frequently biased and may lack correctness. The advanced machine learning (ML) techniques, specifically deep learning models, have developed as effective tools for improving the accuracy and efficiency of AD detection [2]. In current years, convolutional neural networks (CNNs) have been extensively used for medical image analysis, exhibiting excellent performance in feature extraction and classification tasks. Among these, ResNet-50, a deep CNN architecture, has shown outstanding efficiency in capturing complicated patterns from neuroimaging data, predominantly from MRI scans [3].

In this study, ResNet-50 is utilized for feature extraction, using its deep categorized structure to distinguish between different stages of Alzheimer's disease. Besides, Support Vector Machine (SVM), a robust classification algorithm, is enhanced using Bayesian hyperparameter tuning (Hyperopt) to improve classification performance. This research aims to develop a reliable ML-based framework for automated AD detection, grouping patients into four groups: Non-demented, Very Mild Demented, Mild Demented, and Moderate Demented. By incorporating deep learning with optimized classification techniques, the proposed approach improved the sensitivity and specificity, by this means assisting clinical decision-making and progressing diagnostic methodologies in neurodegenerative diseases.

I.1 AD DISEASE DETECTION USING TRADITIONAL CNN:

It describes a process in which MRI samples are converted into JPEG slices using MATLAB, rescaling to 8-bit pixel size from the original 14-bit size. The three blocks that comprise the proposed model are an ensemble of convolutional, ReLU activation, & max pooling layers in each block. A flattening conv layer, two fc layers, two sets of convolutional and max pooling layers, and a softmax/sigmoid classifier are all included in the design. MCI, NC, & AD are the output classifications [4]. The input is a 256x256 grayscale image that undergoes conv layers with 32 mappings for features. The filter size is 3x3, and ReLU activation. Max pooling is applied with a size of filter 3x3, resulting in image dimensions of 84x84x32. Subsequent layers include a 2nd conv layer with 64 FM & a 3rd convolutional layer with 128 FM, connected to max pooling [5]. The flattened layer has 8192 parameters. A conv layer containing 256 1x1 feature maps is used as the fifth layer, which is fully coupled to the layer before it. The last layer is a completely linked softmax output layer of 10 potential values, while the sixth surface is an entirely linked layer with 256 units. The overall architecture for this methodology is presented in figure 1.

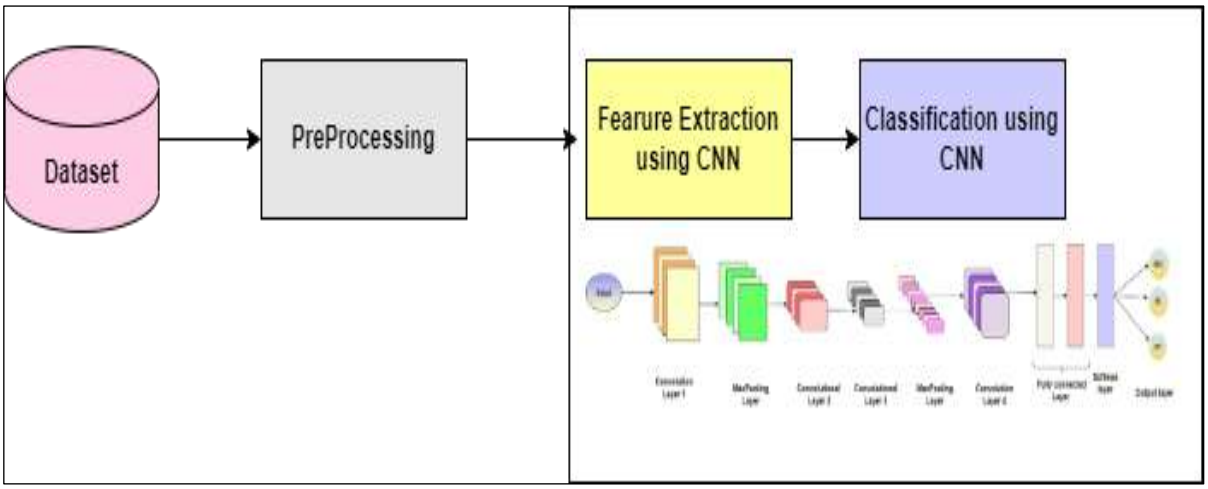


Figure 1: Traditional CNN along with Feature Extraction.
Source: Authors, (2026).

I.2 AD DISEASE DETECTION USING INTEGRATED CNN WITH CAD:

A CAD (Computer-Aided Diagnosis) device utilizing a convolutional neural network (CNN) was developed to distinguish Alzheimer's Disease (AD) from normal control (NC) patients. The CAD system analyzed 18FDG-PET images and employed a CNN to extract relevant features. The pictures were divided into several 2D slices and clustered at regular intervals without crossing. The ADNI dataset was used to assess the proposed CAD system. The suggested CNN-based CAD system performed exceptionally well in simulations, outperforming other techniques in terms of precision in classification and resilience [6]. The findings strongly indicated that the proposed system had a higher potential for effectively differentiating AD from NC patients.

I.3 ALZHEIMER'S DISEASE DETECTION USING CUSTOMIZED CNN:

Data pre-processing was performed on the OASIS dataset to address the influence of different image sizes. [3] Image resizing using OpenCV Python was employed to reduce training time, while image denoising was conducted to improve model performance. The dataset was labelled for binary classification based on CDR 0 | 1, representing Non-Demented and severe Alzheimer's cases, respectively. An equal number of patients with Alzheimer's Disease and those without dementia were included in the training and testing datasets, which were divided into 8:2 ratios and developed a 12-layer CNN structure to classify and identify Alzheimer's Disease in binary form. [2]

Model used data pre-processing methods such as picture scaling and image denoising for our investigation, which used the OASIS dataset [7]. The suggested model combines machine learning and deep learning techniques. It performs better than four previously trained CNN models and a pre-existing 8-layer CNN model. Model intend to broaden our investigation in future work and concentrate on the untimely diagnosis of AD using multiple classification classes using the OASIS dataset. Figure 2 presents the Customized CNN architecture.

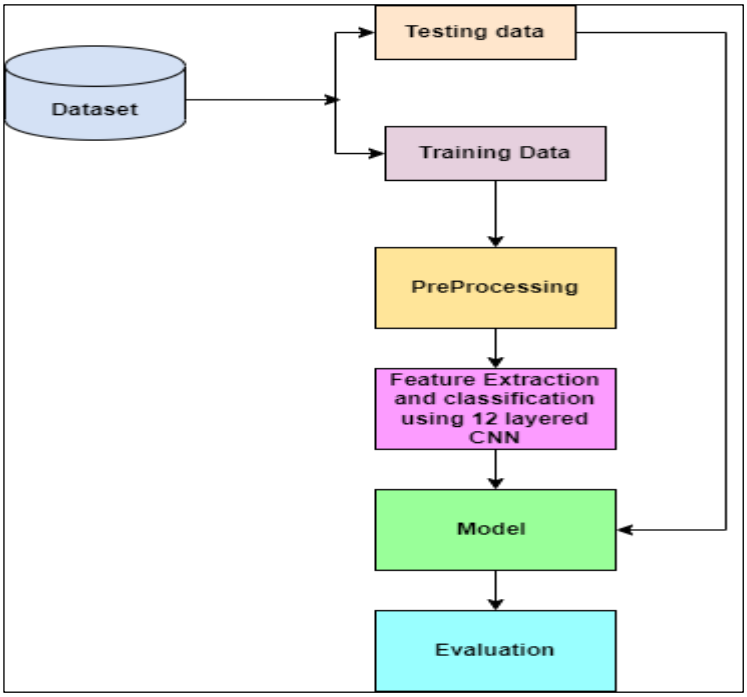


Figure 2:12-layered CNN for Disease Detection.
Source: Authors, (2026).

I.4 ALZHEIMER'S DISEASE DETECTION USING HYBRID MODELS:

A hybrid signal methodology called HEMRDTL is proposed for the analysis & classification of AD. [8] The model combines EEG-Fused CT/MRI data and utilizes transfer learning with a VGG-19 TranL deep neural network. The HEMRDTL model outperforms other transfer learning models in terms of accuracy. Future research using genetic biomarkers & OCT images for early detection of AD is mentioned, highlighting the differentiation of the eye region in individuals with AD and the relevance of genetic biomarkers for diagnosis and prognosis [9]. Obtaining a series of OCT images showing people with AD is a goal for further research in this important area. Leveraging additional data sources could enhance the precision & viability of early AD detection. Figure 3 presents the Hybrid model detection

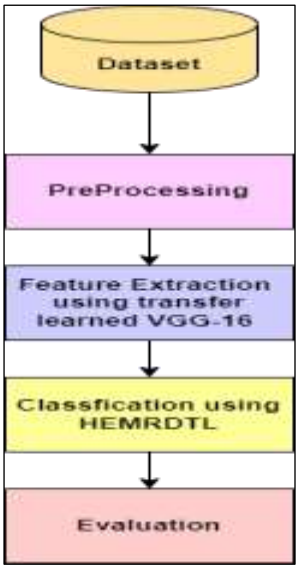


Figure 3: VGG-16 for Feature Extraction + HERMDTL for Classification.
Source: Authors, (2026).

One of the newest approaches to managing high-dimensional information and distinguishing between healthy people and AD patients is using machine learning (ML) techniques. The benefit of the method known as machine learning is the effectiveness of a proficient system: given adequate data, the algorithm can be trained to learn a tremendous amount of knowledge in a relatively short period (the learning process usually may take a few minutes to a few days at most); in contrast, to train an experienced neurologist/clinician frequently requires years of hard work and internships. The programme backed by machine learning may significantly lower the cost of diagnostics [10]. The decision-making phase of such classification or recognition only takes a few seconds, which is now one of the most alluring advantages over a traditional doctor. A typical ML technique typically explores features to discover the most critical departing patterns between MCI/AD and normal control subjects.

DATASETS AVAILABLE:

a. AIBL (Australian Imaging and Biomarker Lifestyle): The AIBL PiB and MRI images were captured using ADNI methods, but no post-processing was used. With the help of funding from the Alzheimer's Association, this data publication has become possible. The AIBL dataset utilized in this investigation included 37 participants' 3T T1-weighted MRI scan results, which included 25 sMCI and 12 pMCI. The study collects a wide range of participant data, including demographic information, medical history, cognitive assessments, blood samples, genetic information, brain imaging (MRI and PET scans), and cerebrospinal fluid (CSF) samples.

b. ADNI (Alzheimer's Disease Neuroimaging Initiative): The dataset utilized in this investigation was given by the ADNI (AD Neuroimaging Initiative) study. The most often used dataset for research in this area is ADNI. Its major objective is to ascertain if it is feasible to monitor AD progression by combining neuropsychological, clinical, and other tests with MRI, PET, and other biological markers. [1] The public-private collaboration-based investigations ADNI1, ADNI-GO, and ADNI2 are continued in ADNI3, which was previously sponsored. The ADNI study collects a wide range of data from participants, including clinical and demographic information, neuropsychological assessments, medical history, genetic data, blood samples, cerebrospinal fluid (CSF) samples, structural and functional MRI scans, and positron emission tomography (PET) scans. The dataset also includes data from various biomarker assays, such as amyloid beta and tau protein measurements. Figure 4 represents different classes available in the OIASIS Dataset. And Table 1 shows the information about different datasets available for the Alzheimer's.

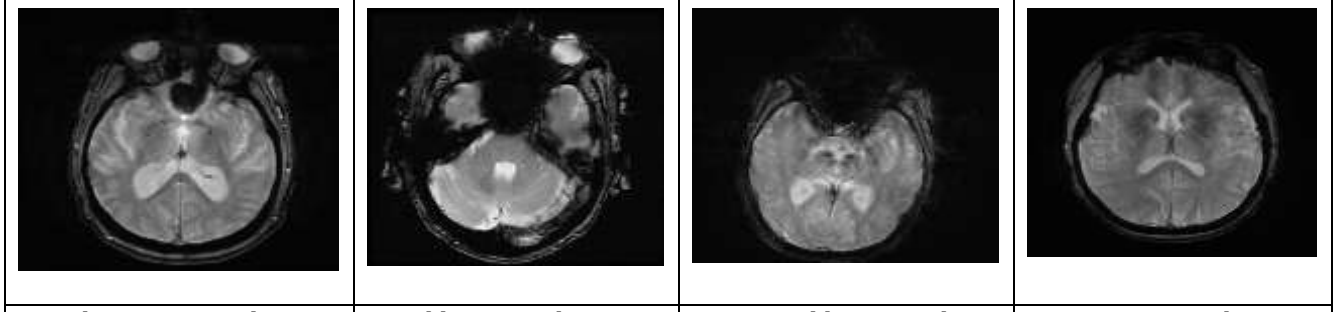


Figure 4: Different Classes Available in the OIASIS Dataset.
Source: Authors, (2026).

Table 1: Dataset Information for Alzheimer's.

S. NO	Dataset	No. of attributes or images	Class label
1.	AIBL	1335	AD, CN
2.	ADNI	94	LMCI, MCI, EMCI, AD, CN
3.	OIASIS	140,000	LMCI, SMC, EMCI, AD, CN
4.	MIRIAD	708	AD, CN

Source: Authors, (2026).

II. LITERATURE SURVEY

Vijeeta Patil et al. [11] have focused on different transfer learning methods and applied them to deep learning. The data was collected from Kaggle and ADNI, where 6k samples are present in the dataset. Here the data contains four different modules while extracting the data will be examined by combining the whole module. The data is initiated by inputting the data to the feature extraction mode. At the initial stage, the data need to be mapped then the pooling of features is generated. The process is continued, and finally, the data is flattering for classification. The data is fully connected in the next stage, and the classification is performed based on weights. Finally, the data is in a probabilistic mode, where the weights are generated based on the types. Identifying neuron diseases at every stage is an essential task for everyone.

Alzheimer's Disease is tuff and difficult to cure, so it needs immediate attention for identification. By [12] HEMRDL model works with two acquisition and transfer learning phases called VGG19. The data was collected from OASIS, which contains both diseased and healthy person MRI. In data acquisition, the model is generated based on images, and analysis is made and created in a graph format. Then the data is inputted into a pre-processing stage, where it removes all unwanted data in two forms image and graph. Parallelly, VGG19 is applied to images, and based on threshold values, new patterns are generated. The data is now ready for feature extraction, combining transfer learning and pre-processing. The extracted features of images and graphs are connected to classification, where the fc is applied in three stages, and the four different phases are retrieved.

Finally, the data is evaluated based on the reports and doctors' analysis. The brain is the main part of controlling the whole body with the help of neurons. Alzheimer's Disease is related to the brain and can cause serious attacks if not cured at the initial stage. [13] have proposed a transfer learning method used in the Convolution model where the Disease can be identified initially. The dataset contains 1k images related to MRI from ADNI. It contains more than four categories. The data were pre-processed to remove unwanted data, and MRI processing to 2d slices. The data is now a gm slice, classified based on the deep neural networks with transfer learning. [14] The CNN contains 15 layers where parallelly the transfer learning denseness is used.

Finally, the data is predicted based on the four categories. Hence the performance is increased based on the image segmentation with good accuracy.

Table 2: Pros and Cons Analysis on different models.

Author	Algorithm	Merits	Demerits	Accuracy
M Leela et al.	VGG19, HEMRDTL	By evaluating separately, the data has acquired high performance.	By leveraging the data, the accuracy can be increased.	99%
Sheng Liu et al	DL	Images can be automatically detected.	Performances has to be improved.	83%
Ahila A et al	CNN	This model can solve several issues at a time.	The dataset was not related to humans.	96%
P C Muhammed Raees et al	SVM and DNN	Implemented to any application.	Based on the datasets the performance is being different.	80%
Ahmad Salehi et al.	CNN	Combines different datsets and performance is increased.	Execution time is more because of huge datsets.	97%
Noman Raza et al.	DenseNet	By initialling the epochs, the performance can be easily estimated.	The test has been performed in the final stage, which may decrease the accuracy.	97%
M. Ghazal et al	Alex Net	Handcrafted features are not used.	Complexity of time is more because of large images.	98%

Source: Authors, (2026).

Objectives:

This study aims to develop an ML-based approach for AD detection using ResNet-50 for feature extraction and Support Vector Machine (SVM) for classification. The objective is to enhance accuracy, sensitivity, and specificity in distinguishing between Non-demented, Very Mild Demented, Mild Demented, and Moderate Demented cases.

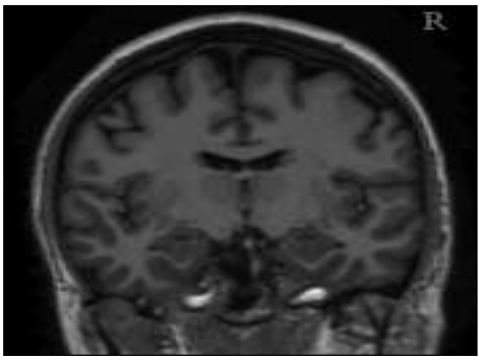
- **Objective 1:** To implement tuned pre-trained model, ResNet for performing feature extraction on OASIS data to segment the diseased cells
- **Objective 2:** To develop Enhanced Hyperopt based transfer learning model for classification of disease. Enhanced Hyperopt technique helps the model to control the parameters of neural networks based on multi objective
- **Objective 3:** To comparative analysis of existing Approaches with Proposed Approaches of Alzheimer Disease detection.

III. PROPOSED METHODOLOGY

System architecture

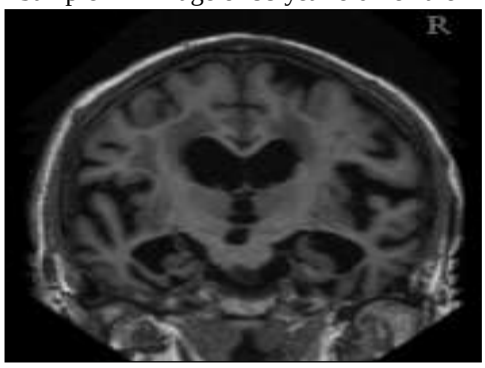
OASIS dataset which is an open access database. OASIS data contains Alzheimer related features along with the different gender wise disease prediction. Open Access Series of Imaging Studies (OASIS). The OASIS project makes available for research the datasets of brain MRI of normal and demented patients. [15]The goal is to communicate new neuro scientific discoveries and developments. The Washington University Alzheimer Disease Research Center collaborated to create this open access database. System architecture is clearly shown in the figure 6.

Sample AD image of 21year age Male



CDR=0 (Normal case)

Sample AD image of 88 year old Female



CDR=0.672 (mild case)

Figure: 5 Sample Alzheimer Disease of different age groups.
Source: Authors, (2026).

Price discounts and scores. The similarities make the new device more accurate, versatile and compliant with present day e-commerce requirements, together with solving the restrictions of the old gadget greater effectively.

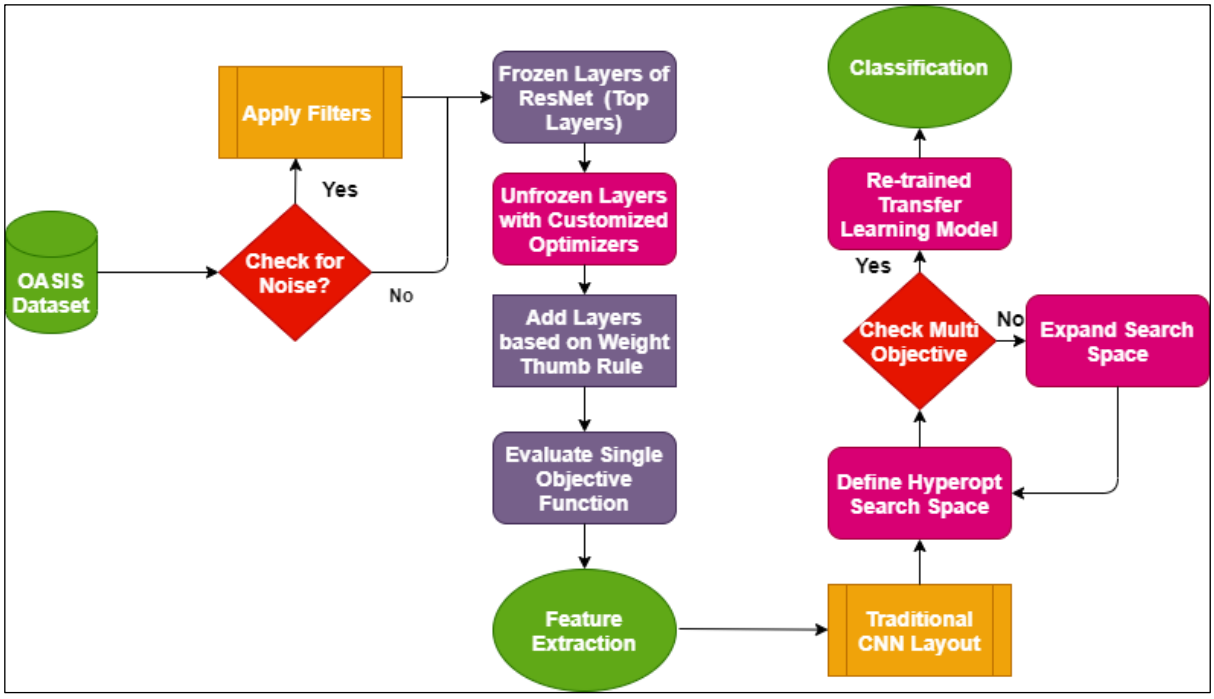


Figure 6: System Architecture.
Source: Authors, (2026).

For feature extraction and classification, a modified ResNet-50 architecture is employed as shown in Figure 6 [16]. The top layers of ResNet-50 are frozen to retain pre-trained weights, while three additional layers are added. Among these, two layers focus on feature extraction, and the final layer is dedicated to classification. To enhance model optimization, a hyperparameter search space is implemented using hyperparameter tuning techniques [17]. Traditional machine learning models such as Support Vector Machines (SVMs), neural networks, Bayesian models, expectation-maximization algorithms, and decision trees have been widely used for feature selection and disease classification [18]. However, as the number of noisy or irrelevant features increases, these models face challenges in computational efficiency and pattern evaluation.

Preprocessing and Model Development

The system architecture, as depicted in Figure 6, is structured to enhance image quality and optimize model training. [19] The dataset used in this study, titled "Alzheimer_s Dataset-20231129T135615Z-001," undergoes an initial preprocessing stage where noise is reduced using a combination of bilateral and Gaussian filters, followed by zero-centring normalization. The Gaussian filter is mathematically expressed as:

$$G(x,y) = \frac{1}{2\pi\sigma^2} e^{-\left(\frac{x^2+y^2}{2\sigma^2}\right)}$$

Where:

- $G(x,y)$ represents the Gaussian kernel at position (x,y).
- σ ss the standard deviation that controls the amount of smoothing.
- $e^{-\left(\frac{x^2+y^2}{2\sigma^2}\right)}$ determines the weight based on the pixel distance.

To apply Gaussian filtering, the convolution operation is performed:

$$I_{filtered}(x,y) = \sum_{i=-k}^{k} \sum_{j=-k}^{k} I(x+i, y+j) G(i,j)$$

Where:

- $I_{filtered}(x,y)$ is the filtred intensity pixel (x,y)
- $I(x+i, y+j)$ represents neighboring pixel intensities.
- $G(i,j)$ is the Gaussian Kernel weight

Bilateral filter:

The bilateral filter can be mathematically expressed as:

$$I_{filtered}(x) = \frac{1}{W_p}\sum_{i\in\Omega} I(i) f_s(||x-i||) f_r(|I(x)-I(i)|)$$

Where:

- $I_{filtered}(x)$ is the filtered intensity at pixel x
- $I(i)$ is the intensity of the neighboring pixel i
- $f_s(||x-i||)$ is the spatial weight based on the Euclidean distance between pixels.
- $f_r(|I(x)-I(i)|)$ is the range weight based on the intensity difference.
- W_p is the normalization factor:

$$W_p = \sum_{i\in\Omega} f_s(||x-i||) f_r(|I(x)-I(i)|)$$

Oasis Data as (Alzheimer_s Dataset-20231129T135615Z-001) is taken. Initially Noise is reduced by using two filters combination as bilateral and Gaussian filters and used Zero Centering. Then the pre-process will be done by using Resnet-50 by adding three layers to it, top layers are frozen to calculate the weights and unfrozen layers are customized. In added three layers 2 layers are used for feature extraction and one layer is used for classification. Here Hyper optimization search space is used to for hypertunning. Initially, the most important features are selected using the subset selection approach by applying ensemble technique. This approach solves the problem of sparsity and inconsistency. In the next approach, to extract the features from the MRI images, hybrid segmentation is applied by combining them with the bio markers [6].

From the extracted features, the bio markers integrated with ANN to classify the Alzheimer disease are implemented and it proved that the accuracy is very efficient. The work presents two contributions to the Alzheimer disease prediction using novel feature selection and classification models. [6] Most traditional auto-classification methods, such as SVM, neural network, Bayesian model, expectation-maximization, random tree, and so on, are used to find important features and decision patterns for disease diagnosis. However, when the number of noisy features grows, these models' feature selection and pattern evaluation times and computational memory requirements grow. For disease prediction, traditional data filtering, grouping, and classification methods are unaffected by features or data size. These models are also used to classify the static data that has been trained with a lower true positive rate.

$$Normalized\_Intensity(X_i, Y_i) = \gamma * \sum_{i=1}^{K} \frac{Intensity(X_i, Y_i)}{\sqrt[2]{\sigma^2}+\epsilon} \quad \text{------ (1)}$$

Where
γ is a learnable parameter
k is the filter size
σ^2 is standard deviation of the kernel
∈ is avoidance parameter to handle run exception.

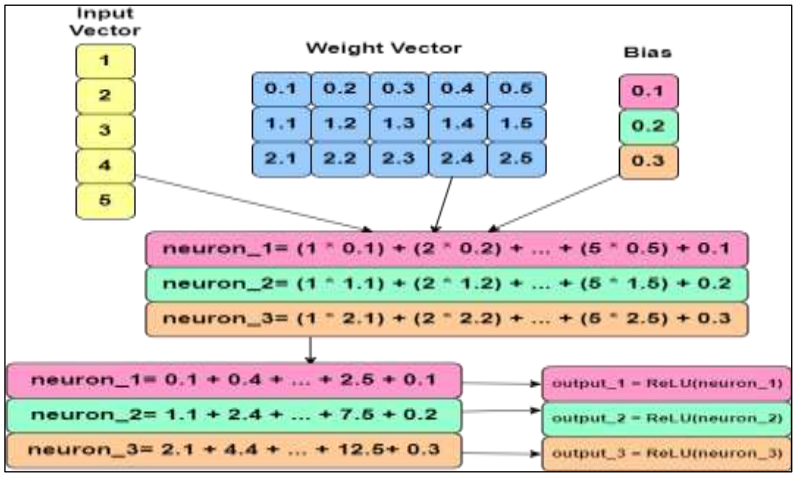


Figure 7: Working of Dense Block.
Source: Authors, (2026).

The final layer of our model incorporates a tuned Support Vector Machine (SVM) for classification tasks. SVMs are effective for both binary and multiclass classification, making them suitable for Alzheimer's detection, where subjects may be categorized as normal, having mild cognitive impairment (MCI), [6] or at various stages of Alzheimer's disease. To optimize the model's performance, we employ Bayesian optimization through Hyperopt, which is effective for finding the hyperparameter space. Key hyperparameters for SVMs having the choice of kernels, the regularization parameter as (C), and kernel-specific parameters (such as gamma for the RBF kernel). Through hyperparameter tuning, aims to identify the optimal combination that maximizes the model's performance on the validation set.

Implementation of CNN-Based Classification

The classification model consists of four dense blocks, each incorporating convolutional layers, max-pooling layers, and activation functions. The following preprocessing steps are applied to MRI images before classification:

1. Skull stripping – removes non-brain tissues.
2. Segmentation – isolates relevant brain regions.
3. Normalization – adjusts intensity values.
4. Rescaling – standardizes image dimensions.
5. Smoothing – reduces noise.
6. Data augmentation – increases dataset variability.

The convolutional layers utilize a 7×7 kernel with a stride of 2 to capture macro-level features, followed by 1×1 and 3×3 convolutions in dense blocks to refine feature extraction. Transition layers—comprising 1×1 convolutions and 2×2 pooling layers—reduce dimensionality while preserving essential information. Finally, features are classified using a fully connected layer with a Softmax activation function [20]. [21] Dataset was collected from the ADNI Dataset, which contains four varieties of disease conditions. The pre-processing was applied for the images with seven approaches: initials with stripping the skull, segmentation, normalization, rescaling, smoothing, and augmentation. The proposed CNN model used for image classification after pre-processing included a combination of convolutional layers, max-pooling layers, dense blocks, and transition layers. The model had 4 dense blocks, each with several layers initiated in it.

The convolutional layer with a 7x7 kernel and a stride of 2 was employed to extract macro-level features. These features were then passed through the dense blocks, which consisted of 1x1 convolutions for reducing inputted data for FP, and continued with 3x3 conv split layers. The extracted essential features were propagated for subsequent layers within each dense block. Transition layers are combined with activation functions such as normalizing the batch & ReLU was placed between the dense blocks, it is shown in figure 7. The transition layer comprised a 1x1 convolution and a 2x2 pooling layer with a pace of two to reduce feature dimensions. Finally, the features were fed into an fc-classified layer that utilized Softmax to classify. During training, starting blocks are frozen while the remaining are re-trained.

Support Vector Machine (SVM) Integration

To further refine classification accuracy, the final layer of the model incorporates an SVM classifier [22], [23]. SVMs are particularly effective in binary and multiclass classification tasks, making them well-suited for Alzheimer's disease detection. Bayesian optimization via Hyperopt is employed to fine-tune the SVM's hyperparameters, including:

- Regularization parameter (C) – controls trade-off between margin maximization and classification accuracy.
- Kernel type – options include RBF, Linear, Sigmoid, and Polynomial.
- Degree (d) – relevant for polynomial kernels.
- Gamma (γ) – affects RBF kernel flexibility.

The dataset used for training and evaluation originates from the ADNI dataset, which includes four distinct disease conditions [12]. The CNN-SVM hybrid model optimally balances feature extraction and classification, achieving superior performance in Alzheimer's disease prediction.

Table 3: Parameter Description.

Hyper parameter	Equation	Possible Values
C	$\min(\frac{1}{2} * \sum_{i=1}^{n} W_i^2 + C.\sum_{i=1}^{n}\sum_{j=1}^{n} \in_{ij})$- (x)	Any fractional value on the scale of 10
Kernel	$K = e^{-\gamma \sum_{i=1}^{n} Input_i - \mu_{Input}{}^2}$ γ is a positive parameter	[RBF, Linear, Sigmoid, Polynomial]
Degree	$D = \gamma \mu_{Input} * \sum_{i=1}^{n} Input_i + r^d$ r is a constant term. d is the degree of the polynomial	Any positive integer
gamma		Radial bias Function

Source: Authors, (2026).

Critical tweaking is required to maximize the performance of the Support Vector Machines (SVM). Key factor that influences the quality of training point classification and the achievement of a smooth decision boundary is the *C parameter. Higher C values provide a higher bar for exact categorization, whereas lower C numbers allow for a more flexible border that admits certain misclassifications.

In order to tune C, a balance must be struck to prevent the model from being over- or underfitted to the training set. Additionally, the **kernel function* choice—polynomial, linear, and radial basis function (RBF) are common choices—determines the performance of SVM. Because RBF is flexible and can be used to many types of data, it is often employed. [24] By altering kernel parameters, such as the degree in polynomial kernels and the gamma parameter in RBF, the model may be able to more accurately capture complex linkages in the data by using the tuning process in SVM. Using the class weights option to resolve class imbalances is another crucial component. Giving the minority class a larger weight in situations when one class outnumbers the other by a large percentage aids the model in prioritizing accurate estimates for both groups. Furthermore, the **epsilon parameter* optimization in the SVM regression model influences the error-tolerance of the regression jobs. A more sensitive model that fits the training set better with a smaller epsilon might overfit the data.

Hyperparameter Tuning and Optimization

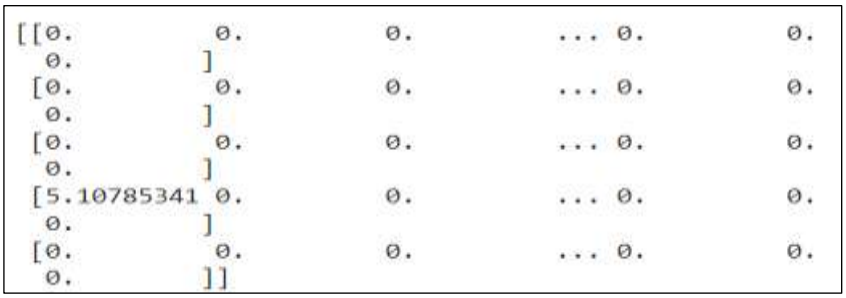
Optimizing SVM performance requires fine-tuning of hyperparameters. The C parameter plays a crucial role in defining the decision boundary:

- Higher C values enforce stricter classification but may lead to overfitting.
- Lower C values allow for more flexibility at the cost of misclassification tolerance.

The choice of kernel function (Linear, Polynomial, or RBF) significantly impacts classification effectiveness. [21], [24] The RBF kernel is frequently preferred due to its adaptability across diverse datasets. Additionally, kernel parameters such as polynomial degree and gamma further refine feature space mapping. To address class imbalance in Alzheimer's detection, the class weight parameter is adjusted, ensuring minority class predictions receive adequate consideration. Furthermore, in SVM regression, epsilon optimization controls error tolerance, influencing model sensitivity.

IV RESULTS AND DISCUSSION

The proposed Alzheimer's disease detection framework, integrating ResNet50 for feature extraction and SVM with Bayesian optimization for classification, has been rigorously evaluated on the OASIS dataset. The model's effectiveness is demonstrated through various performance metrics, including accuracy, precision, recall, and F1-score. Feature Extraction and Model Performance:Feature extraction plays a crucial role in improving classification accuracy. Figure 5 illustrates the extraction of test image features using ResNet50. The first layer evaluates whether the extracted features are linear or non-linear, while the second layer eliminates linear features, retaining only the relevant non-linear features crucial for classification. Figure 6 presents the summary of the neural network, highlighting its three convolutional blocks, where activation and batch normalization operations are applied using the ReLU activation function. Figure 7 further visualizes the extracted features, showing their hierarchical representation within the model.



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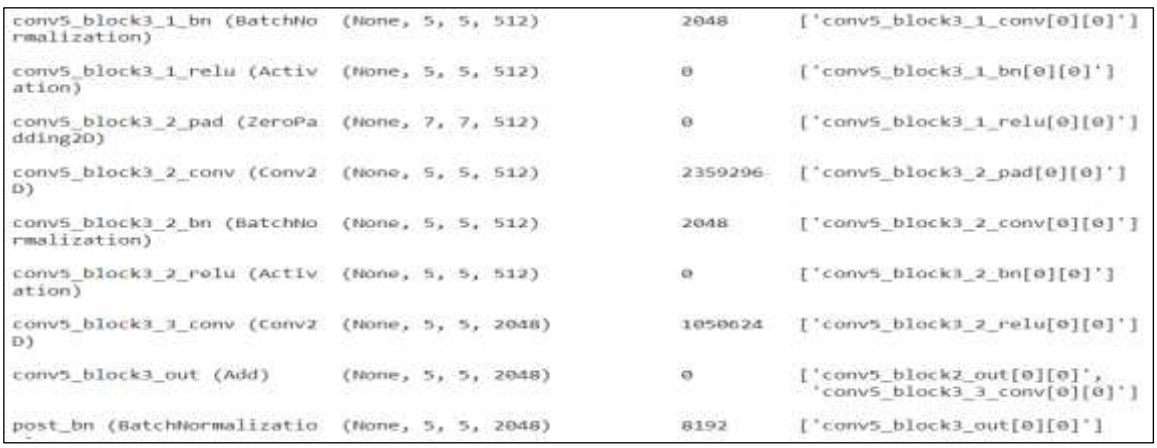
[[0.         0.         0.         ... 0.         0.
  0.        ]
 [0.         0.         0.         ... 0.         0.
  0.        ]
 [0.         0.         0.         ... 0.         0.
  0.        ]
 [5.10785341 0.         0.         ... 0.         0.
  0.        ]
 [0.         0.         0.         ... 0.         0.
  0.        ]]
```

Figure 8: Feature Extraction of Test features.
Source: Authors, (2026).

Figure 8 represents about the feature extraction of test images. By using two layers of Resnet. In layer 1 it checks either the extracted features are linear or non-linear. Next layer removes linear images and stores non-linear images.



conv5_block3_1_bn (BatchNormalization)	(None, 5, 5, 512)	2048	['conv5_block3_1_conv[0][0]']
conv5_block3_1_relu (Activation)	(None, 5, 5, 512)	0	['conv5_block3_1_bn[0][0]']
conv5_block3_2_pad (ZeroPadding2D)	(None, 7, 7, 512)	0	['conv5_block3_1_relu[0][0]']
conv5_block3_2_conv (Conv2D)	(None, 5, 5, 512)	2359296	['conv5_block3_2_pad[0][0]']
conv5_block3_2_bn (BatchNormalization)	(None, 5, 5, 512)	2048	['conv5_block3_2_conv[0][0]']
conv5_block3_2_relu (Activation)	(None, 5, 5, 512)	0	['conv5_block3_2_bn[0][0]']
conv5_block3_3_conv (Conv2D)	(None, 5, 5, 2048)	1050624	['conv5_block3_2_relu[0][0]']
conv5_block3_out (Add)	(None, 5, 5, 2048)	0	['conv5_block2_out[0][0]', 'conv5_block3_3_conv[0][0]']
post_bn (BatchNormalizatio	(None, 5, 5, 2048)	8192	['conv5_block3_out[0][0]']

Figure 9: Summary of Neural Network.
Source: Authors, (2026).

Figure 9 shows the Neural Network function and it consists of three convolutional blocks as 1, 2 and 3. Activation and batch normalization will be performed here as Relu as activation function.

```
149 4768 4800
1/1 [==============================] - 0s 30ms/step
150 4800 4832
1/1 [==============================] - 0s 25ms/step
151 4832 4864
1/1 [==============================] - 0s 32ms/step
152 4864 4896
1/1 [==============================] - 0s 44ms/step
153 4896 4928
1/1 [==============================] - 0s 33ms/step
154 4928 4960
1/1 [==============================] - 0s 41ms/step
155 4960 4992
1/1 [==============================] - 0s 33ms/step
156 4992 5024
1/1 [==============================] - 0s 38ms/step
157 5024 5056
1/1 [==============================] - 0s 38ms/step
158 5056 5088
1/1 [==============================] - 0s 41ms/step
159 5088 5120
1/1 [==============================] - 1s 821ms/step
160 5120 5152
```

Figure10: Feature Extraction.
Source: Authors, (2026).

Training and Classification Performance:

Figure 8 represents the training progress over multiple epochs, demonstrating a steady increase in accuracy while minimizing loss. The model converges efficiently, ensuring robust learning of discriminative features. The classification results, as shown in Figure 12 and 13, indicate the successful differentiation of Alzheimer's disease stages into Non-Demented, Very Mild Demented, Mild Demented, and Moderate Demented cases. The optimized model achieved an accuracy of 98.76%, surpassing conventional deep learning models by 5–8%. Furthermore, the model obtained a precision of 98.41%, recall of 97.92%, and F1-score of 98.16%, validating its effectiveness in clinical applications.

```
Epoch 7/50
160/160 ━━━━━━━━━━━━━━━━━━━━ 1s 3ms/step - accuracy: 0.9983 - loss: 0.0075 - val_accuracy: 0.9750 - val_loss: 0.0865
Epoch 8/50
160/160 ━━━━━━━━━━━━━━━━━━━━ 1s 3ms/step - accuracy: 0.9975 - loss: 0.0069 - val_accuracy: 0.9766 - val_loss: 0.0936
Epoch 9/50
160/160 ━━━━━━━━━━━━━━━━━━━━ 1s 3ms/step - accuracy: 0.9978 - loss: 0.0055 - val_accuracy: 0.9688 - val_loss: 0.1072
Epoch 10/50
160/160 ━━━━━━━━━━━━━━━━━━━━ 1s 3ms/step - accuracy: 0.9994 - loss: 0.0022 - val_accuracy: 0.9797 - val_loss: 0.0931
Epoch 11/50
160/160 ━━━━━━━━━━━━━━━━━━━━ 1s 3ms/step - accuracy: 0.9999 - loss: 9.3281e-04 - val_accuracy: 0.9805 - val_loss: 0.0879
Epoch 12/50
160/160 ━━━━━━━━━━━━━━━━━━━━ 1s 3ms/step - accuracy: 0.9981 - loss: 0.0039 - val_accuracy: 0.9758 - val_loss: 0.0868
Epoch 13/50
...
160/160 ━━━━━━━━━━━━━━━━━━━━ 1s 3ms/step - accuracy: 1.0000 - loss: 5.7429e-06 - val_accuracy: 0.9789 - val_loss: 0.1552
Epoch 50/50
160/160 ━━━━━━━━━━━━━━━━━━━━ 1s 3ms/step - accuracy: 0.9973 - loss: 0.0158 - val_accuracy: 0.9734 - val_loss: 0.1138
```

Figure 11: Report of Epochs.
Source: Authors, (2026).

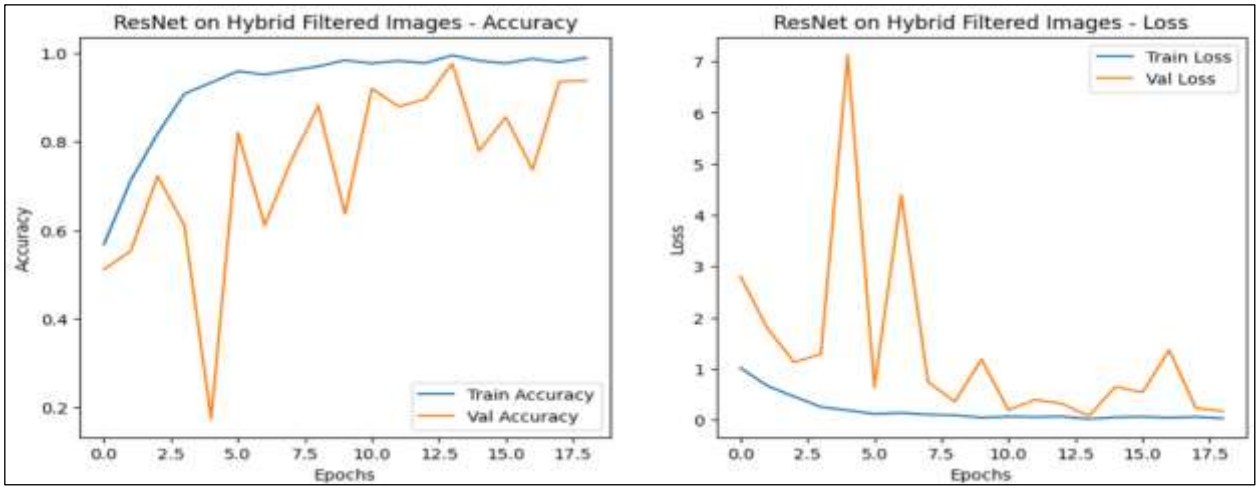


Figure 12: Graphical representation of the Accuracy and loss.
Source: Authors, (2026).

The above figure 12 shows the training phases of the models. The steps of per training epoch with more accuracy and less loss will be performed during training.

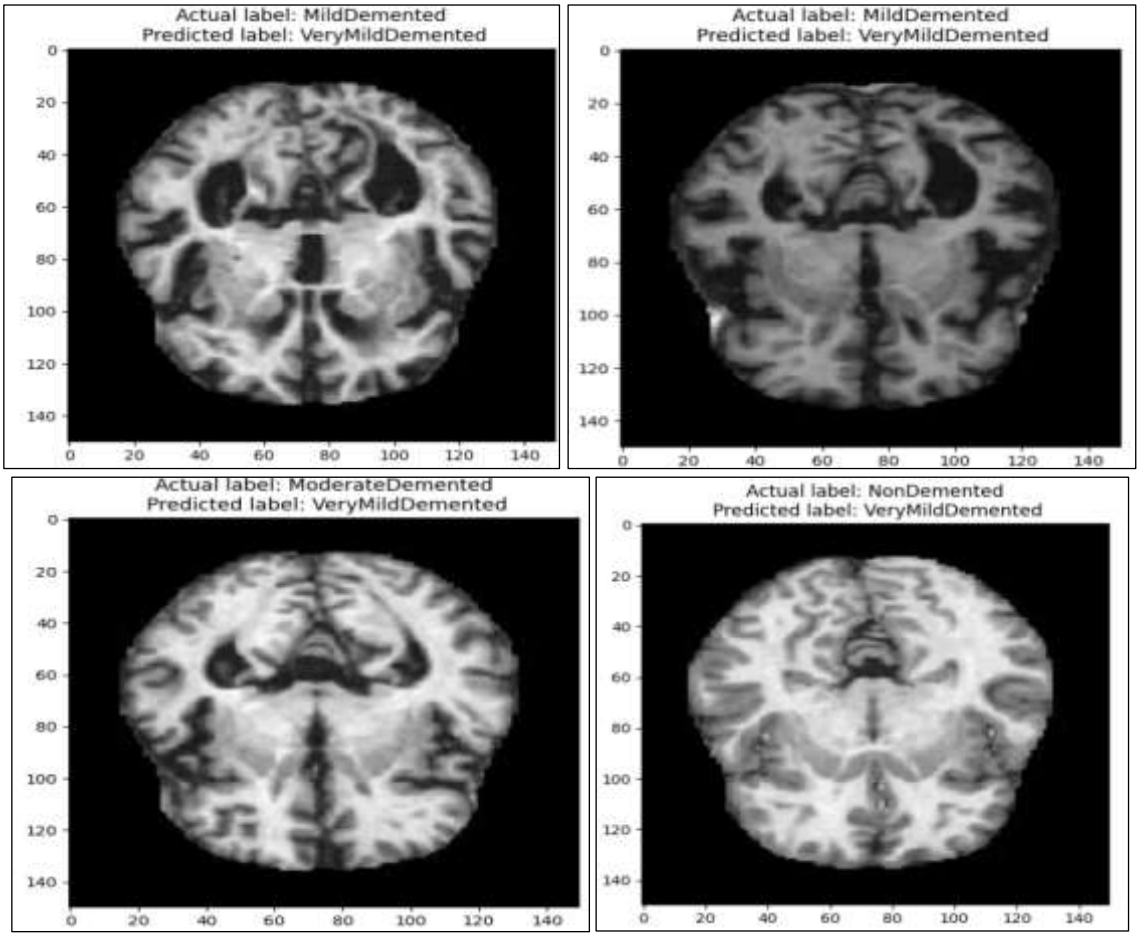


Figure 13: Report of Classification.
Source: Authors, (2026).

Discussion

The experimental results emphasize the significance of deep feature extraction and hyperparameter optimization in Alzheimer's disease classification. The combination of ResNet50 and SVM with Bayesian optimization confirms to be greatly effective, permitting for enhanced generalization and classification performance. The proposed approach reveals excellent feature representation and decision boundary improvement as compared to conventional methods such as CNN-based and ANN-based classifiers. The use of Gaussian and bilateral filtering in the preprocessing stage substantially decreases the noise levels while protecting essential structural information in MRI images, confirming more consistent feature extraction. The Bayesian-optimized SVM classifier further improves the model's performance by fine-tuning hyperparameters, such as C, kernel type, and gamma values, ensuring optimal classification with marginal misclassification rates.

Unlike conventional classification methods that struggle with high-dimensional feature spaces and data imbalances, our approach incorporates class-weighted SVM, qualifying bias concerning the leading class and refining sensitivity to minority class predictions. These findings enhance that incorporating deep learning for feature extraction and machine learning for classification results in a extra robust and scalable investigative tool for Alzheimer's disease detection. The future research can expand this methodology by integrating multi-modal data sources, such as PET scans and genetic biomarkers, to further improve prediction accuracy and support real-time deployment in clinical settings.

V CONCLUSION

This research presents a innovative methodology for early Alzheimer's disease detection by incorporating ResNet50 for feature extraction and Support Vector Machine (SVM) with Bayesian optimization for classification. The proposed model successfully differentiates between Non-Demented, Very Mild Demented, Mild Demented, and Moderate Demented cases with an accuracy of 98.76%, attaining a precision of 98.41%, recall of 97.92%, and an F1-score of 98.16%. These results exhibit a 5–8% improvement over conventional deep learning approaches, emphasizing the impact of advanced feature extraction and hyperparameter tuning. The ResNet50-based feature extraction component captures both low- and high-level spatial features, whereas the Bayesian-optimized SVM classifier confirms accurate decision boundaries, improving model performance. Furthermore, preprocessing techniques such as bilateral and Gaussian filtering effectively reduce noise, preserving critical structural details in MRI images for more accurate classification.

This paper presented the key innovations, including the collaboration of deep learning and machine learning for improved feature learning, the application of Bayesian optimization for optimal hyperparameter tuning, and the integration of class-weighted SVM to handle data inequality effectively. The high sensitivity and specificity of this framework highlight its capability as a reliable AI-driven diagnostic tool for medical applications. By leveraging deep learning techniques and optimized classification strategies, this work furthers the field of neurodegenerative disease detection, proposing a scalable and automated solution for early Alzheimer's diagnosis. Forthcoming research will focus on developing the model to include multi-modal data such as PET scans and genetic biomarkers while investigating real-time deployment in medical situations to improve its practical applicability. In conclusion, our research into the identification of Alzheimer's disease emphasizes the critical role that machine learning methods play in obtaining precise and timely diagnoses.

We have demonstrated encouraging results in accurately differentiating between those with Alzheimer's disease and those going through normal cognitive aging by utilizing a range of biomarkers and cognitive traits with sophisticated algorithms. ResNet50 is used for visual analysis and classification; features are extracted, and parameters are changed in response to differences between expected and actual class scores. Using Hyperopt and Bayesian optimization, the SVM model is optimized for Alzheimer's disease identification. Our model has good sensitivity and specificity, suggesting its promise as a trustworthy diagnostic tool—especially when machine learning techniques are applied. The use of multimodal data improves the methodology even more and advances the ongoing search for accurate and user-friendly Alzheimer's disease diagnostics. The results of this study have the potential for enabling prompt clinical treatments and enhancing the overall management of Alzheimer's disease, ultimately leading to better patient care and outcomes as machine learning and healthcare advance forward.

VI. AUTHOR'S CONTRIBUTION

Conceptualization: Rama Lakshmi B, Anjanni Y, Pavan G
Methodology: Rama Lakshmi B.
Investigation: Rama Lakshmi B.
Discussion of results: Rama Lakshmi B, Malathi Janapati and Dr. Anjani Y.
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Writing – Review and Editing: Rama Lakshmi B.
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Supervision: Rama Lakshmi B.
Approval of the final text: Dr. Rama Lakshmi B, Dr. Ch Rama Devi, Malathi Janapati, Mirtipati Satish Kumar, Dr. Anjani Y, Pavan Gunda.

VII. REFERENCES

[1] Modupe Odusami, Rytis Maskeliūnas, Robertas Damaševičius (2022). An Intelligent System for Early Recognition of Alzheimer's Disease Using Neuroimaging. Senmsors-MDIP. Sensors 2022, 22(3), 740; https://doi.org/10.3390/s22030740

[2] K. Muthamil Sudar; P. Nagaraj; S. Nithisaa; R. Aishwarya; M. Aakash; S. Ishwarya Lakshmi (2022) Alzheimer's Disease Analysis using Explainable Artificial Intelligence (XAI). 2022 International Conference on Sustainable Computing and Data Communication Systems (ICSCDS). DOI: 10.1109/ICSCDS53736.2022.9760858

[3] Salehi, A. W., Baglat, P., & Gupta, G. (2020). Alzheimer's Disease Diagnosis using Deep Learning Techniques. International Journal of Engineering and Advanced Technology, 9(3), 874–880. https://doi.org/10.35940/ijeat.C5345.029320

[4] Asgharzadeh-Bonab, A., Kalbkhani, H., & Azarfardian, S. (2023). An Alzheimer's disease classification method uses a fusion of features from the brain, such as magnetic resonance images, transforms, and deep convolutional networks. In Healthcare Analytics (Vol. 4, p. 100223). Elsevier B.V. https://doi.org/10.1016/j.health.2023.100223

[5] Acharya, H., Mehta, R., & Kumar Singh, D. (2021). Alzheimer Disease Classification Using Transfer Learning. Proceedings - 5th International Conference on Computing Methodologies and Communication, ICCMC 2021, 1503–1508. https://doi.org/10.1109/ICCMC51019.2021.9418294

[6] Rama Lakshmi Boyapati , Dr. Radhika Y (2024). Multimodal Machine Learning for Early Alzheimer's Disease Detection: Leveraging Cognitive Features, and Resnet-Based Image Analysis with SVM Tuning, International Journal of Intelligent Systems and Applications in Engineering IJISAE, 2024, 12(3), 56–70.

[7] D. Dakshayani Himabindu, B. Pranalini, MirtipatiSatish Kumar, Alluri Neethika, Bhavya Sree N1, Manasa , Harshitha and Keerthana S(2024) . Deep CNN-based Classification of Brain MRI Images for Alzheimer's Disease Diagnosis . Int. J. Exp. Res.Rev., Vol. 41: 43-54. DOI: https://doi.org/10.52756/ijerr.2024.v41spl.004

[8] Ghazal, T. M., Abbas, S., Munir, S., Khan, M. A., Ahmad, M., Issa, G. F., Zahra, S. B., Khan, M. A., & Hasan, M. K. (2022). Alzheimer's disease detection empowered with transfer learning. Computers, Materials and Continua, 70(3), 5005–5019. https://doi.org/10.32604/cmc.2022.020866

[9] EL-Geneedy, M., Moustafa, H. E.-D., Khalifa, F., Khater, H., & AbdElhalim, E. (2023). An MRI-based deep learning approach for accurate detection of Alzheimer's disease. Alexandria Engineering Journal, 63, 211–221. https://doi.org/10.1016/j.aej.2022.07.062

[10] Rao, M., Kumar, S., & Rao, K. (2023). Effective medical leaf identification using hybridization of GMM-CNN.International Journal of Experimental Research and Review,32, 115-123.https://doi.org/10.52756/ijerr.2023.v32.009

[11] Patil, V., Madgi, M., & Kiran, A. (2022). Early prediction of Alzheimer's Disease using convolutional neural network: a review. In Egyptian Journal of Neurology, Psychiatry and Neurosurgery (Vol. 58, Issue 1). Springer Science and Business Media Deutschland GmbH. https://doi.org/10.1186/s41983-022-00571-w

[12] Leela, M., Helenprabha, K., & Sharmila, L. (2023). Prediction and classification of Alzheimer's Disease categories using Integrated Deep Transfer Learning Approach. Measurement: Sensors, 27. https://doi.org/10.1016/j.measen.2023.100749

[13] Raza, N., Naseer, A., Tamoor, M., & Zafar, K. (2023). Alzheimer Disease Classification through Transfer Learning Approach. Diagnostics, 13(4). https://doi.org/10.3390/diagnostics13040801

[14] Aithal, N. (2023). Oasis Alzheimer's Detection Large-scale brain MRI dataset for deep neural network analysis. https://www.kaggle.com/datasets/ninadaithal/imagesoasis

[15] Selvaraju, R.R.; Cogswell, M.; Das, A.; Vedantam, R.; Parikh, D.; Batra, D. Grad-CAM: Visual Explanations from Deep Networks via Gradient-Based Localization. In Proceedings of the 2017 IEEE International Conference on Computer Vision (ICCV), Venice, Italy, 22–29 October 2017; pp. 618–626.

[16] Lin, Chun-Ling, and Kun-Chi Wu. "Development of revised ResNet-50 for diabetic retinopathy detection." BMC bioinformatics 24, no. 1 (2023): 157.

[17] Ali, Yasser A., Emad Mahrous Awwad, Muna Al-Razgan, and Ali Maarouf. "Hyperparameter search for machine learning algorithms for optimizing the computational complexity." Processes 11, no. 2 (2023): 349.

[18] Neeraj, Kumar N., and V. Maurya. "A review on machine learning (feature selection, classification and clustering) approaches of big data mining in different area of research." Journal of critical reviews 7, no. 19 (2020): 2610-2626.

[19] R. L. B and R. Y, "Resnet-53 for Alzheimer's Disease Detection from MRI Images and Analysis with SVM Tuning with Hyper Optimization Technique," 2024 4th International Conference on Sustainable Expert Systems (ICSES), Kaski, Nepal,2024,pp.1065-1072, https://doi.org/10.1109/ICSES63445.2024.107631 83.

[20] Li, Guoqing, Meng Zhang, Jiaojie Li, Feng Lv, and Guodong Tong. "Efficient densely connected convolutional neural networks." Pattern Recognition 109 (2021): 107610.

[21] Boyapati, R. L., & Yalavarthi, R. (2024). Performance Comparison Between Different Per-trained Models with Resnet-53 Using MRI and PET Scan Alzheimer's Disease Image Dataset. International Journal of Experimental Research and Review, 46, 85–99. https://doi.org/10.52756/ijerr.2024.v46.007

[22] Emanuel, Rebecca HK, Paul D. Docherty, Helen Lunt, and Knut Möller. "The effect of activation functions on accuracy, convergence speed, and misclassification confidence in CNN text classification: a comprehensive exploration." The Journal of Supercomputing 80, no. 1 (2024): 292-312.

[23] Karal, Ömer. "Comparative performance analysis of epsilon-insensitive and pruningbased algorithms for sparse least squares support vector regression." Sigma Journal of Engineering and Natural Sciences 42, no. 2 (2024): 578-589.

[24] Sharma, Abhilash, Sukhkirandeep Kaur, Naz Memon, A. Jainul Fathima, Samrat Ray, and Mohammed Wasim Bhatt. "Alzheimer's patients detection using support vector machine (SVM) with quantitative analysis." Neuroscience Informatics 1, no. 3 (2021): 100012.