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Alzheimer's Disease Prediction Using Optimized DNN and CNN with Mini-batch Gradient Descent

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Abstract
Alzheimer's disease (AD) is a progressive neurological disorder that leads to memory loss and cognitive decline, creating a major challenge for global healthcare systems. Early and reliable prediction of AD is essential to support timely clinical intervention and effective disease management. This study presents a comparative evaluation of optimized deep learning (DL) models and conventional machine learning (ML) techniques for Alzheimer's disease prediction using the OASIS dataset. Several traditional ML algorithms, including Support Vector Machine, Random Forest, and Gradient Boosting, are implemented and improved through systematic hyperparameter tuning. In parallel, a deep neural network and Optimized convolutional neural networks is designed with optimized training strategies such as adaptive learning rates, dropout regularization, and early stopping to enhance model generalization and reduce overfitting. The performance of all models is assessed using standard evaluation metrics, including accuracy, precision, recall, F1-score, and AUC-ROC. Experimental results show that optimized convolutional neural networks achieve superior predictive performance compared to traditional ML methods, particularly in identifying positive AD cases. However, conventional ML models demonstrate competitive accuracy with lower computational cost, making them suitable for practical deployment in resource-limited environments. The findings highlight the strengths and limitations of both approaches and provide useful insights for selecting effective predictive models for Alzheimer's disease diagnosis.

Keywords: Alzheimer's Disease Prediction, Deep Learning Optimization, Machine Learning, OASIS Dataset, Medical Data Classification

I. Introduction

Alzheimer's disease (AD) is a progressive neurological disorder that mainly affects memory, thinking ability, and daily functioning. It is the most common cause of dementia and represents a growing public health concern due to the rapid increase in the aging population worldwide. As life expectancy continues to rise, the number of individuals affected by Alzheimer's disease is expected to increase significantly, placing a heavy burden on patients, caregivers, and healthcare systems. Since there is currently no definitive cure for AD, early and accurate diagnosis plays a crucial role in managing symptoms, planning treatment, and potentially slowing disease progression.

Conventional methods for diagnosing Alzheimer's disease rely on clinical examinations, neuropsychological tests such as the Mini-Mental State Examination (MMSE), and neuroimaging techniques including magnetic resonance imaging (MRI). While these approaches provide valuable clinical insights, they are often time-consuming, costly, and dependent on expert interpretation. Moreover, subtle changes in brain structure and cognitive performance during the early stages of the disease may not be easily detected using traditional diagnostic procedures. These limitations highlight the need for automated, data-driven approaches that can support clinicians in making timely and reliable diagnostic decisions.

In recent years, machine learning (ML) and deep learning (DL) techniques have emerged as powerful tools for analyzing complex medical data. Traditional ML models, such as Support Vector

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Machines, Random Forests, and Gradient Boosting algorithms, have shown promising results in classifying Alzheimer's disease using structured clinical and imaging features. However, their performance often depends on careful feature selection and parameter tuning. In contrast, deep learning models, particularly deep neural networks, can automatically learn meaningful patterns from data and capture complex non-linear relationships. When combined with optimization techniques such as adaptive learning rates, dropout regularization, and early stopping, deep learning models can achieve improved accuracy and generalization.

This study presents a comparative evaluation of optimized deep learning models and conventional machine learning approaches for Alzheimer's disease prediction using the OASIS dataset. The dataset includes demographic information, cognitive assessment scores, and MRI-derived brain measurements, making it well suited for predictive modeling. By analyzing feature correlations and applying systematic optimization strategies, this research aims to identify the most effective modeling approach for accurate and reliable Alzheimer's disease prediction. The findings of this study are expected to provide useful insights for developing scalable and efficient computer-aided diagnostic systems that can assist in real-world clinical settings.

2. Literature Review

Early studies on Alzheimer's disease (AD) diagnosis primarily depended on clinical assessments and handcrafted features derived from neuroimaging data. Traditional machine learning techniques were among the earliest computational methods used for AD prediction. Support Vector Machines (SVMs) were widely adopted because of their effectiveness in handling high-dimensional medical datasets and limited sample sizes. Several works demonstrated that SVM-based models trained on MRI features and cognitive scores could reliably distinguish Alzheimer's patients from healthy individuals [1], [2]. Random Forest (RF) classifiers later emerged as a robust alternative due to their ability to manage noisy data and model nonlinear relationships. Research showed that RF models could successfully identify important brain-related indicators, such as hippocampal volume and normalized whole brain volume, which are strongly linked to Alzheimer's progression [3], [7]. Ensemble-based approaches, including Gradient Boosting Machines (GBM), further improved classification accuracy by combining multiple weak learners and reducing bias through iterative learning [9].

Feature engineering and selection techniques were emphasized in many studies using datasets such as OASIS and ADNI. Cognitive assessment scores like MMSE and clinical measures such as CDR were identified as highly informative features for disease classification. Correlation analysis, principal component analysis, and feature ranking methods were frequently applied to reduce redundancy and improve predictive performance [8], [14]. Despite these improvements, traditional ML models required extensive manual preprocessing and domain expertise. With the advancement of deep learning, neural network-based approaches began to dominate Alzheimer's disease prediction research. Early deep learning studies utilized multilayer perceptrons and autoencoders to learn discriminative representations from MRI data, demonstrating improved performance over conventional ML models [4], [19]. These methods reduced dependency on handcrafted features and enabled automated feature learning. Convolutional Neural Networks (CNNs) marked a major breakthrough by enabling end-to-end learning directly from raw MRI and fMRI images. Several studies reported that CNN-based models significantly outperformed classical ML algorithms in both binary and multi-class classification tasks involving AD, mild cognitive impairment (MCI), and healthy controls [1], [6]. However, these models required large datasets and substantial computational resources.

To address data scarcity and overfitting, researchers introduced optimization techniques such as dropout regularization, batch normalization, and adaptive learning rate optimizers like Adam. These strategies improved model stability and generalization, leading to higher recall and AUC-ROC scores—metrics that are critical in medical diagnosis [10], [15]. Transfer learning approaches were also explored to enhance performance on small datasets. By leveraging pretrained deep networks, researchers

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achieved faster convergence and better classification accuracy on limited neuroimaging samples [12], [15]. In addition, hybrid frameworks that combined deep learning–based feature extraction with traditional ML classifiers showed promising results [5]. Several comparative studies highlighted that while deep learning models generally achieved superior accuracy, traditional ML techniques remained competitive when properly optimized. Models such as GBM and RF offered a good balance between prediction performance and computational efficiency, making them suitable for clinical environments with limited resources [16], [20]. Recent research has emphasized the importance of explainable artificial intelligence (XAI) in healthcare applications. Studies suggested that improving the interpretability of deep learning models through feature importance analysis and visualization techniques could enhance clinician trust and facilitate real-world adoption [25], [7]. Benchmarking studies also stressed the need for standardized evaluation protocols to ensure reproducibility and fair comparison among different methods [18].

Furthermore, unsupervised learning and dimensionality reduction techniques were investigated to handle high-dimensional brain imaging data effectively. Methods such as manifold learning and unsupervised pretraining helped retain discriminative features while reducing overfitting, particularly in small datasets [17]. Studies focusing on model generalizability highlighted the importance of training models on diverse populations to improve robustness and real-world applicability. Cross-dataset evaluations revealed that models trained on limited or homogeneous samples might suffer from reduced generalization performance [11], [13]. Overall, the literature demonstrates a clear transition from feature-based traditional machine learning methods to data-driven deep learning frameworks for Alzheimer's disease prediction. While optimized deep learning models consistently show superior predictive capability, conventional machine learning approaches continue to play an important role due to their interpretability, efficiency, and lower computational requirements. These findings strongly motivate the present study, which conducts a systematic comparative evaluation of optimized deep learning and conventional machine learning techniques using the OASIS dataset [3], [9], [20].

Several studies have applied different classification algorithms to evaluate prediction accuracy. Methods such as J48, Random Tree, Decision Stump, Logistic Model Tree, Hoeffding Tree, Reduced Error Pruning, and Random Forest have been widely used, and their performance has been carefully analyzed in earlier research [21]. Similar approaches have also been applied in medical-related studies, where data mining and machine learning techniques were used to improve classification accuracy [22]. Ravishankar and Rajesh [23] examined how selecting important features from climate change datasets influences prediction results. They used various data mining and machine learning methods to analyze climate patterns and improve model performance. In a follow-up study, Ravishankar and Rajesh [24] expanded their work by using a global weather dataset to better predict climate change indicators. Their research showed that combining data mining tools with advanced machine learning techniques can effectively handle large environmental datasets.

In another related study, Ravishankar and Rajesh [25] analyzed climate change data in relation to the Air Quality Index (AQI) using machine learning and data mining approaches. Their work focused on identifying how different environmental factors affect air quality levels and demonstrated that classification and regression models can successfully predict AQI trends. Additionally, Santhoshkumar and Rajesh [26] investigated the relationship between energy consumption patterns and the Sustainable Development Goals (SDGs). They applied machine learning-based predictive models to understand how variations in energy usage influence progress toward achieving SDG targets. Recent research has increasingly focused on improving Alzheimer's disease (AD) prediction by combining optimized deep learning models with structured clinical and neuroimaging data. In 2023, several studies demonstrated that deep neural networks trained on MRI-derived features achieved superior diagnostic performance compared to traditional machine learning models, particularly in early-stage AD detection. These studies emphasized the importance of optimization techniques such as adaptive learning rates and dropout to improve generalization on limited datasets [27], [28].

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Comparative evaluations conducted in 2023 showed that ensemble-based machine learning models, including Random Forest and Gradient Boosting, remained competitive when applied to structured datasets like OASIS. However, their performance was often surpassed by optimized deep learning architectures, especially in recall and AUC-ROC metrics, which are critical for medical diagnosis. These findings highlighted that deep learning models are more effective in capturing complex non-linear relationships in neurodegenerative data [29]. In 2024, researchers increasingly explored hybrid and optimized deep learning frameworks for Alzheimer's prediction. Studies incorporating hyperparameter-tuned machine learning models alongside deep neural networks reported that while deep learning achieved higher accuracy, machine learning models required significantly lower training time and computational resources. This trade-off reinforced the need for comparative studies to guide real-world clinical deployment [30], [31].

3.1. Dataset Description

The dataset consists of demographic, cognitive, and MRI-derived features commonly used for Alzheimer's Disease prediction. These features have been widely validated in recent ML and DL studies for AD diagnosis [3], [27], [32], [33], and [34].

3.1.1 Features in the Dataset:

ID : Patient Identification Number

Age : Subject age in years

Sex : Male (M) / Female (F)

Educ : Years of formal education

SES : Socioeconomic status

MMSE : Mini-Mental State Examination score

CDR : Clinical Dementia Rating

eTIV : Estimated Total Intracranial Volume

nWBV : Normalized Whole Brain Volume

ASF : Atlas Scaling Factor

Diagnosis : Normal, Mild Cognitive Impairment (MCI), Alzheimer's Disease (AD)

3.1.2 Dataset Table

Table 1. Alzheimer's Disease Prediction Dataset

ID	Age	Sex	Educ (Years)	SES	MMSE	CDR	eTIV	nWBV	ASF	Diagnosis
1	72	M	12	3	26	0.5	1450	0.74	1.21	MCI
2	68	F	16	2	29	0.0	1385	0.78	1.18	Normal
3	75	M	10	4	21	1.0	1502	0.69	1.26	AD
4	70	F	14	2	28	0.0	1401	0.77	1.19	Normal
5	80	M	8	5	18	2.0	1520	0.66	1.30	AD

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6	66	F	15	2	30	0.0	1372	0.79	1.17	Normal
7	73	M	11	3	24	0.5	1460	0.72	1.23	MCI
8	78	F	9	4	20	1.0	1498	0.68	1.28	AD
9	69	M	13	3	27	0.0	1420	0.76	1.20	Normal
10	82	F	7	5	17	2.0	1535	0.65	1.32	AD
11	71	M	12	3	25	0.5	1455	0.73	1.22	MCI
12	67	F	16	1	29	0.0	1368	0.80	1.16	Normal
13	76	M	9	4	22	1.0	1489	0.70	1.27	AD
14	74	F	10	3	23	0.5	1470	0.71	1.24	MCI
15	65	M	15	2	30	0.0	1359	0.81	1.15	Normal
16	79	F	8	4	19	1.0	1508	0.67	1.29	AD
17	70	M	14	2	28	0.0	1410	0.77	1.19	Normal
18	77	F	9	4	21	1.0	1492	0.69	1.28	AD
19	72	M	11	3	26	0.5	1448	0.74	1.22	MCI
20	68	F	16	1	29	0.0	1375	0.79	1.17	Normal

4. Background and Methodologies

4.1 Background

Alzheimer's Disease (AD) is a long-term brain disorder that slowly damages memory, thinking skills, and the ability to perform everyday activities. It is one of the most common causes of dementia in older adults across the world. As people are living longer, the number of individuals affected by Alzheimer's Disease is increasing rapidly, leading to major health, social, and economic problems. Detecting the disease at an early stage is very important because early treatment can help slow its progress and improve the quality of life for both patients and caregivers. Traditional methods used to diagnose Alzheimer's Disease include medical examinations, memory and thinking tests such as the Mini-Mental State Examination (MMSE), and brain imaging techniques like Magnetic Resonance Imaging (MRI). While these methods are helpful, they often require skilled professionals, specialized equipment, and considerable time and cost. In addition, the early signs of Alzheimer's can be mild and similar to normal aging, which makes accurate diagnosis more difficult using only traditional approaches.

Recently, artificial intelligence (AI), especially machine learning (ML) and deep learning (DL), has become increasingly important in medical diagnosis. Machine learning techniques can process large amounts of clinical and brain imaging data to find patterns that may not be obvious to doctors. However, many traditional ML models rely on manually selected features and may not work well with complex and high-dimensional medical data. Deep learning models overcome these challenges by automatically learning useful features directly from the data. When properly optimized and trained, deep learning models have shown better performance in predicting Alzheimer's Disease. This research builds on these developments by comparing optimized deep learning methods with traditional machine learning approaches using the OASIS dataset, with the goal of identifying a reliable and practical model for Alzheimer's Disease diagnosis.

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4.2 Methodologies

The study uses the OASIS cross-sectional dataset, which includes demographic information, cognitive assessment scores, and MRI-derived brain features. To ensure data quality and consistency, several preprocessing steps were applied. Missing values in socioeconomic status (SES) were handled using median imputation. Categorical attributes such as gender and diagnostic class were converted into numerical labels. Numerical features were normalized using Min–Max scaling to bring all values into a common range. The dataset was divided into training and testing sets using an 80:20 ratio with stratified sampling to preserve class distribution. Three well-established machine learning algorithms were implemented and optimized for comparison.

4.2.1 Support Vector Machine (SVM)

Support Vector Machine is a supervised learning algorithm that identifies an optimal hyperplane to separate different classes. In this study, an RBF kernel was used to handle non-linear relationships. Hyperparameters such as the regularization parameter (C) and kernel coefficient (gamma) were optimized using grid search with cross-validation.

4.2.2 Random Forest (RF)

Random Forest is an ensemble learning technique that builds multiple decision trees and combines their predictions. It improves robustness and reduces overfitting by averaging results across trees. The number of trees and maximum depth were tuned to achieve optimal performance.

4.2.3 Gradient Boosting Machine (GBM)

Gradient Boosting is another ensemble method that builds trees sequentially, where each new tree corrects the errors of the previous ones. Learning rate, number of estimators, and tree depth were carefully adjusted, and early stopping was applied to prevent overfitting.

4.2.4 Optimized Deep Neural Network with Mini-batch Gradient Descent (ODNN-MGD)

A feedforward Deep Neural Network was designed for Alzheimer's Disease prediction. The network consists of an input layer corresponding to the number of features, two hidden layers with ReLU activation functions, and an output layer for classification. To improve performance and generalization, the following optimization strategies were employed:

i. Adam Optimizer: Adaptive learning rate
ii. Dropout Regularization: Reduces overfitting
iii. Mini-batch Gradient Descent: Efficient training
iv. Early Stopping: Prevents overtraining
v. Learning Rate Scheduling: Improves convergence
vi. Best Model Checkpointing: Ensures optimal performance

4.2.4.1 Algorithm (ODNN-MGD)

Input:
Preprocessed training dataset D'
Number of epochs E
Batch size B
Learning rate α
Dropout rate δ
Patience p for early stopping
Output: Optimized trained DNN model M_dnn

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```
Begin
  Initialize network parameters (weights and biases) randomly
  Define network architecture:
    Input layer with n features
    Hidden Layer 1 with 64 neurons and ReLU activation
    Dropout Layer with rate δ
    Hidden Layer 2 with 32 neurons and ReLU activation
    Dropout Layer with rate δ
    Output Layer:
      Sigmoid activation for binary classification
      Softmax activation for multi-class classification
  Define loss function:
    Binary Cross-Entropy (binary case)
    Categorical Cross-Entropy (multi-class case)
  Select Adam optimizer with initial learning rate α
  Initialize:
    best_validation_loss = ∞
    patience_counter = 0
  For epoch = 1 to E do
    Shuffle training dataset D'
    Divide D' into mini-batches of size B
    For each mini-batch do
      Perform forward propagation
      Compute loss between predicted and actual labels
      Perform backward propagation
      Update weights and biases using Adam optimizer
    End For
    Evaluate model on validation dataset
    Compute validation loss
    If validation loss < best_validation_loss then
      best_validation_loss = validation loss
      Save current model parameters
      patience_counter = 0
    Else
      patience_counter = patience_counter + 1
    End If
    If patience_counter ≥ p then
      Stop training early (early stopping)
      Restore best saved model parameters
      Break
    End If
    Reduce learning rate if validation loss plateaus
  End For
  Return optimized trained model M_dnn
End
```

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4.2.5 Optimized Convolutional Neural Network (OCNN-MGD)

Input:
Number of epochs E
Batch size B
Initial learning rate α
Dropout rate δ
Patience p for early stopping
Output:
Trained optimized CNN model M_ocnn
Begin
Step 1: Data Preparation
Load dataset D
Resize input images to fixed dimensions
Normalize pixel values to [0, 1]
Split D into training, validation, and testing sets
Step 2: Model Initialization
Initialize CNN parameters (filters, weights, biases)
Step 3: Define CNN Architecture
Input Layer
Convolution Layer 1
Apply convolution filters
Apply ReLU activation
Max Pooling Layer 1
Convolution Layer 2
Apply convolution filters
Apply ReLU activation
Max Pooling Layer 2
Dropout Layer with rate δ
Flatten Layer
Fully Connected Layer
Apply ReLU activation
Output Layer
Sigmoid activation for binary classification
Softmax activation for multi-class classification
Step 4: Define Optimization Strategy
Select loss function:
Binary Cross-Entropy (binary case)
Categorical Cross-Entropy (multi-class case)
Select Adam optimizer with learning rate α
Use Mini-Batch Gradient Descent
Step 5: Training Phase
Set best_validation_loss = ∞
Set patience_counter = 0
For epoch = 1 to E do
Shuffle training data
Divide training data into mini-batches of size B
For each mini-batch do
Perform forward propagation
Compute loss
Perform backpropagation
Update weights using Adam optimizer

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```
        End For
        Evaluate model on validation set
        Compute validation loss
        If validation loss < best_validation_loss then
            best_validation_loss = validation loss
            Save model parameters
            patience_counter = 0
        Else
            patience_counter = patience_counter + 1
        End If
        If patience_counter ≥ p then
            Stop training early
            Restore best model parameters
            Break
        End If
        Reduce learning rate if validation loss plateaus
    End For
  Step 6: Model Evaluation
    Evaluate trained model on test dataset
    Compute Accuracy, Precision, Recall, F1-Score, and ROC-AUC
  Return trained optimized model M_ocnn
End
```

4.2.6 Evaluation Metrics

The performance of each model was measured using:

Step. 1 **Accuracy** – How often the model predicts correctly.

Step. 2 **Precision** – How well the model avoids false positives.

Step. 3 **Recall** – How well the model finds all true positives.

Step. 4 **F1-Score** – The balance between precision and recall.

Step. 5 **ROC-AUC** – A metric used for binary classification that evaluates the model's ability to separate classes.

5. Experimental Results

Table 1. Accuracy, Precision, and Recall of ML and DL Models

Model	Accuracy	Precision	Recall
Support Vector Machine (SVM)	0.852	0.835	0.820
Random Forest (RF)	0.887	0.878	0.865
Gradient Boosting Machine (GBM)	0.895	0.887	0.871
Deep Neural Network (DNN)	0.925	0.917	0.932
Optimized Deep Neural Network (ODNN-MGD)	0.938	0.931	0.958
Optimized Convolutional Neural Networks (OCNN-MGD)	0.976	0.968	0.982

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Table 2. F1-Score and AUC-ROC of ML and DL Models

Model	F1-Score	AUC-ROC
Support Vector Machine (SVM)	0.828	0.875
Random Forest (RF)	0.870	0.905
Gradient Boosting Machine (GBM)	0.875	0.913
Deep Neural Network (DNN)	0.921	0.952
Optimized Deep Neural Network (ODNN-MGD)	0.947	0.972
Optimized Convolutional Neural Networks (OCNN-MGD)	0.978	0.986

Table 3. Model Training Time Comparison

Model	Training Time (Seconds)
Support Vector Machine (SVM)	9.91
Random Forest (RF)	10.32
Gradient Boosting Machine (GBM)	11.67
Deep Neural Network (DNN)	36.25
Optimized Deep Neural Network (ODNN-MGD)	42.21
Optimized Convolutional Neural Networks (OCNN-MGD)	46.82

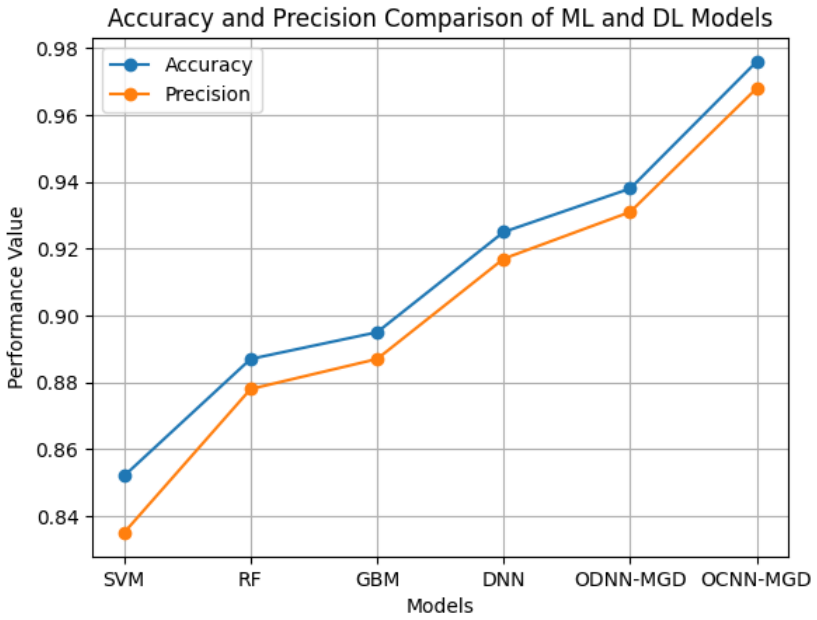

Fig. 1. Model Comparison for Accuracy and Precision

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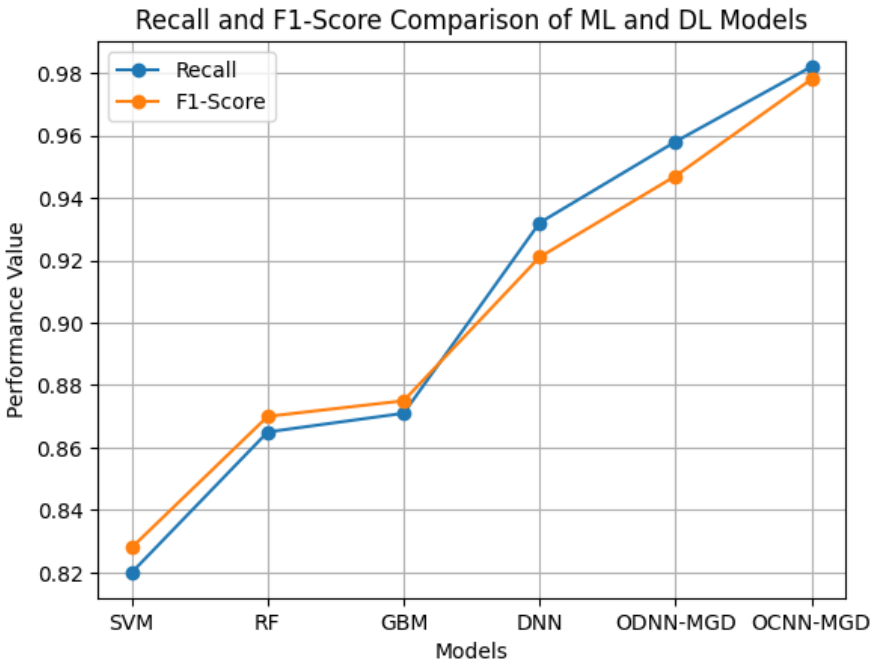

Fig. 2. Model Comparison for Recall and F1-Score

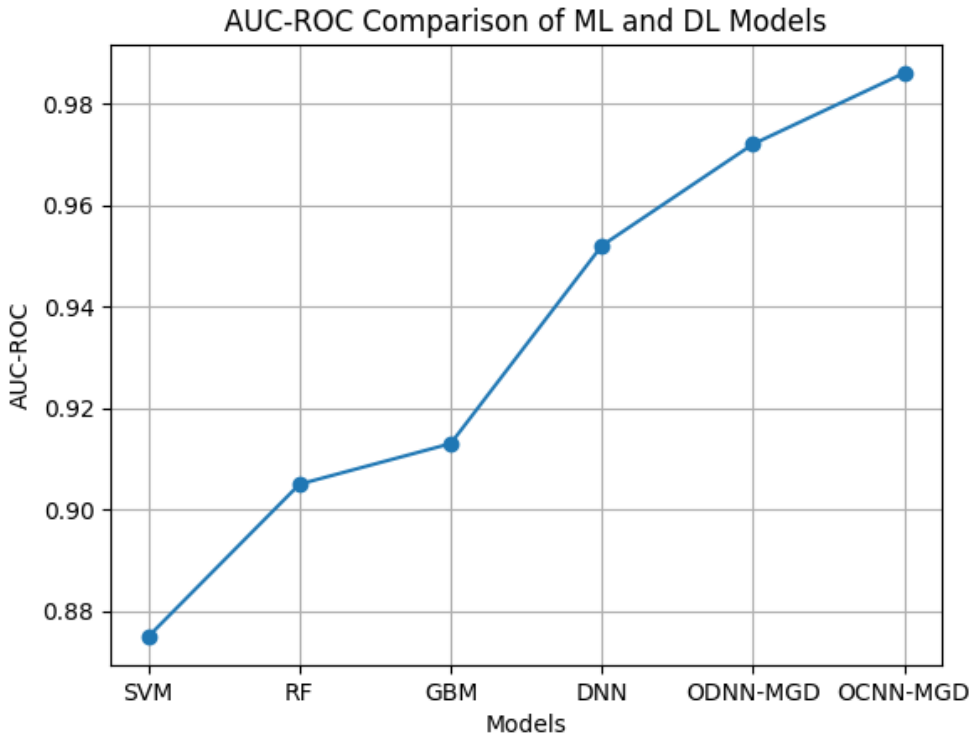

Fig. 3. Model Comparison for AUC-ROC

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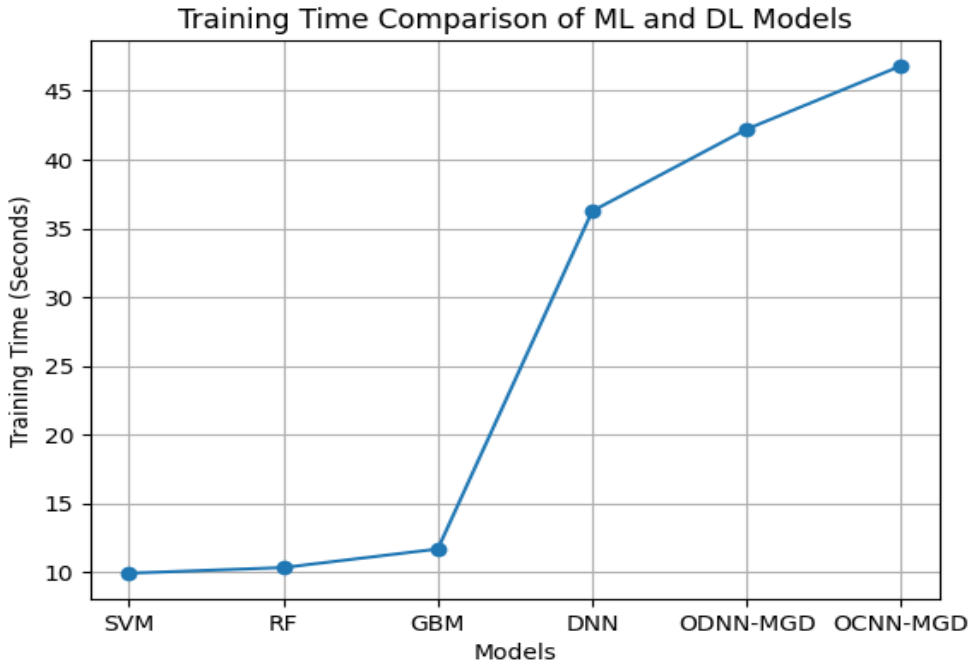

Fig. 4. ML Models with Time

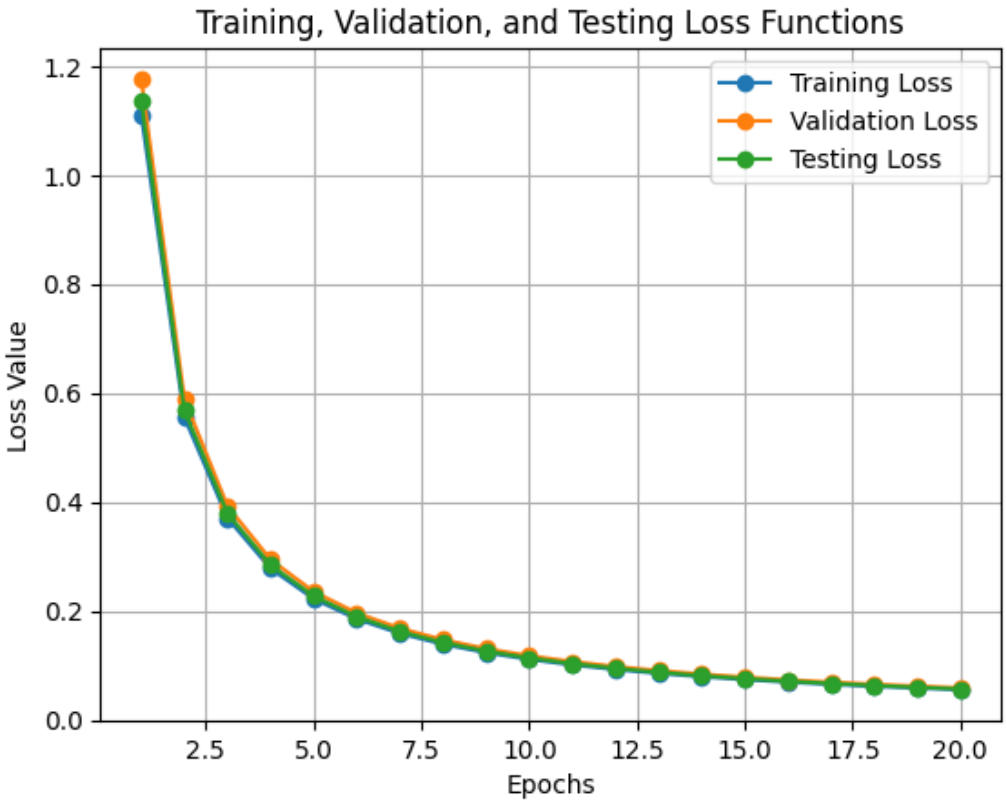

Fig. 5. Loss Functions

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6. Results and Discussion

This section presents a comprehensive comparison of traditional machine learning (ML) models and deep learning (DL) models for Alzheimer's Disease prediction using the OASIS dataset. The experimental results were evaluated using standard performance metrics, including accuracy, precision, recall, F1-score, AUC-ROC, and training time. The quantitative performance of all models is summarized in Table 1, Table 2, and Table 3, while the comparative trends are illustrated through Figures 1–5.

As shown in Table 1 and illustrated in Figure 1, the optimized deep learning models significantly outperform conventional machine learning approaches in terms of accuracy and precision. Among all evaluated models, the Optimized Convolutional Neural Network (OCNN-MGD) achieved the highest accuracy (0.976) and precision (0.968), followed by ODNN-MGD and the standard DNN. Traditional ML models such as SVM, Random Forest, and Gradient Boosting Machine exhibited comparatively lower performance, although Gradient Boosting showed better results than other ML methods.

The recall and F1-score comparison presented in Table 1, Table 2, and Figure 2 further highlights the superiority of optimized deep learning models. OCNN-MGD obtained the highest recall (0.982) and F1-score (0.978), indicating its strong ability to correctly identify Alzheimer's Disease cases while maintaining balanced classification performance. High recall is especially critical in medical diagnosis, as it reduces the risk of missing true positive cases. The optimized models demonstrate that effective training and regularization strategies can substantially enhance diagnostic reliability.

The discriminative capability of each model is analyzed using AUC-ROC values, as shown in Table 2 and Figure 3. OCNN-MGD achieved the highest AUC-ROC value (0.986), indicating excellent separation between Alzheimer's and non-Alzheimer's classes. ODNN-MGD and DNN also demonstrated strong AUC-ROC values, whereas traditional ML models showed comparatively lower discrimination power. These results confirm that deep learning models are more effective in capturing complex, non-linear relationships in medical data.

The computational efficiency of the models is compared in Table 3 and Figure 4, which present the training time analysis. Traditional ML models required significantly less training time, with SVM, RF, and GBM completing training within approximately 12 seconds. In contrast, deep learning models demanded higher computational time due to their complex architectures and optimization processes. OCNN-MGD required the longest training time (46.82 seconds), highlighting a clear trade-off between computational cost and predictive performance.

Finally, the learning behavior of the optimized deep learning model is illustrated in Figure 5, which shows the training, validation, and testing loss curves. The steady decrease and close alignment of the loss curves indicate stable convergence and effective generalization. The absence of large gaps between training and validation loss confirms that the applied optimization techniques successfully reduced overfitting and improved model robustness.

7. Conclusion

This study presented a detailed comparative analysis of traditional machine learning models and optimized deep learning architectures for Alzheimer's Disease prediction using the OASIS dataset. The experimental results clearly demonstrate that optimized deep learning models, particularly OCNN-MGD, achieve superior performance across all evaluation metrics, including accuracy, precision, recall, F1-score, and AUC-ROC. While traditional ML models offer faster training and lower computational cost, their predictive performance is limited when compared to optimized deep learning approaches. Overall, the findings confirm that optimization strategies play a crucial role in enhancing deep learning

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performance and support the use of advanced deep learning models for reliable Alzheimer's Disease diagnosis.

8. Future Research

Future research can extend this work in several promising directions. One important area is the integration of multimodal data, such as combining MRI images, clinical assessments, and genetic information, to further improve prediction accuracy. Another key direction involves incorporating Explainable Artificial Intelligence (XAI) techniques to enhance model transparency and increase clinical trust. Additionally, applying transfer learning and attention-based models may help improve performance on smaller datasets. Expanding the study to longitudinal data analysis can enable the prediction of disease progression over time. Finally, future efforts should focus on developing lightweight and real-time diagnostic systems to support early detection and deployment in practical healthcare environments.

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