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Developing An Intelligent Recommendation Learning Framework For Autism: Integrating Neural Networks, K-Means Clustering, And Gradient Descent Optimization

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Abstract: Autism Spectrum Disorder (ASD) is a neurodevelopmental condition characterized by significant heterogeneity in behavioral and neurological patterns, making accurate diagnosis and personalized intervention challenging. Traditional diagnostic approaches primarily focus on binary classification, which is insufficient for severity-aware treatment planning. This paper presents an end-to-end deep learning–based framework for ASD detection, severity stratification, and personalized intervention recommendation. The proposed methodology integrates supervised Deep Neural Network (DNN) classification with unsupervised K-Means clustering applied to latent feature representations to identify intra-class ASD subgroups. Following classification, only ASD-positive samples are clustered to discover severity- and behavior-based subgroups corresponding to mild, moderate, and severe ASD profiles. These subgroups are subsequently mapped to personalized intervention strategies using AR/VR-based therapeutic content. The proposed framework enables accurate ASD detection, captures hidden heterogeneity, and supports precision-driven intervention planning. Experimental evaluation demonstrates that clustering on deep latent features provides meaningful stratification beyond binary diagnosis, establishing a robust foundation for adaptive and intelligent ASD support systems.

Keywords: Autism Spectrum Disorder, Deep Neural Network, K-Means Clustering, Severity Stratification, Latent Feature Learning, Personalized Intervention, AR/VR Therapy

1. INTRODUCTION

Autism Spectrum Disorder (ASD) is a complex neurodevelopmental condition characterized by impairments in social communication, restricted interests, and repetitive behavioral patterns. The manifestation of ASD varies significantly across individuals in terms of cognitive ability, language development, sensory processing, and behavioral characteristics, making it a highly heterogeneous disorder [1]. This variability presents major challenges for both diagnosis and intervention, as no two individuals with ASD exhibit identical symptom profiles. Consequently, traditional diagnostic approaches that rely primarily on behavioral observations and clinical assessments are often subjective, time-consuming, and dependent on expert interpretation [2].

Over the past decade, computational approaches using machine learning and deep learning have gained increasing attention in ASD research. Neuroimaging modalities such as functional Magnetic Resonance Imaging (fMRI), structural MRI, and behavioral biomarkers have been widely explored to develop automated ASD detection systems [3]. Deep Neural Networks (DNNs), in particular, have demonstrated strong potential in learning complex nonlinear relationships from high-dimensional neuroimaging data, outperforming conventional machine learning techniques such as Support Vector Machines and Random Forests in several studies [4]. However, most existing computational models focus primarily on binary classification—distinguishing ASD from typically developing (TD) individuals—without considering the diverse range of severity levels and behavioral subtypes within the ASD population [5].

While binary classification provides a useful screening tool, it is insufficient for clinical decision-making and personalized intervention planning. Individuals diagnosed with ASD require different therapeutic strategies depending on their cognitive level, language ability, sensory sensitivity, and social responsiveness [6]. For example, children with mild ASD may benefit more from social interaction training, whereas those with severe ASD may require communication-focused therapies. Despite this need, very few computational models integrate ASD detection with severity stratification and personalized intervention recommendation in a unified framework [7].

Recent studies have suggested that unsupervised learning techniques, such as clustering, can help identify hidden subgroups within ASD populations based on behavioral and neuroimaging features [8]. K-Means clustering, in particular, has been used to reveal distinct ASD phenotypes without requiring predefined labels, making it suitable for modeling ASD heterogeneity [9]. Furthermore, the use of latent feature representations learned by deep networks has been shown to improve clustering performance compared to raw input features, as these representations capture high-level abstract patterns related to brain connectivity and behavior [10].

In parallel, advancements in Augmented Reality (AR) and Virtual Reality (VR) technologies have opened new possibilities for ASD intervention. AR/VR-based therapeutic systems provide immersive, controlled, and interactive environments that can enhance social communication, attention, and sensory regulation in children with ASD [11]. However, most existing AR/VR interventions follow a generic approach rather than being tailored to individual severity levels or behavioral profiles [12].

To address these limitations, this research proposes an end-to-end framework that integrates:

1. Deep learning–based ASD classification,
2. Unsupervised severity stratification using K-Means clustering on latent features, and
3. Personalized AR/VR-based intervention recommendation based on identified subgroups.

By combining supervised and unsupervised learning within a single pipeline, the proposed approach moves beyond traditional binary diagnosis and enables data-driven, severity-aware, and personalized ASD support. The overall framework is illustrated in the methodology workflow and is designed to bridge the gap between computational diagnosis and practical therapeutic intervention

2. RELATED WORKS

Automated diagnosis and analysis of Autism Spectrum Disorder (ASD) using computational techniques have gained significant attention in recent years. Early studies primarily relied on traditional machine learning algorithms such as Support Vector Machines (SVM), k-Nearest Neighbors (k-NN), and Random Forest for ASD classification using neuroimaging and behavioral data. For instance, SVM-based approaches were widely used due to their robustness in high-dimensional feature spaces; however, they often struggled to capture complex nonlinear relationships in brain imaging data [13], [14]. Similarly, conventional Artificial Neural Networks (ANNs) showed moderate improvements over classical classifiers but were limited by shallow architectures and insufficient feature representation capabilities [15].

With the advent of deep learning, researchers have increasingly adopted Deep Neural Networks (DNNs) for ASD detection, particularly using resting-state fMRI and structural MRI data from the ABIDE dataset. Heinsfeld et al. demonstrated that deep learning models could achieve superior classification performance compared to traditional machine learning techniques, highlighting the effectiveness of hierarchical feature learning for ASD prediction [16]. Dvornek et al. further extended this by integrating phenotypic and neuroimaging features using deep recurrent neural networks, achieving improved diagnostic accuracy [17]. Similarly, Parisot et al. introduced graph-based deep learning models to capture brain connectivity patterns, demonstrating the potential of advanced neural architectures in ASD classification [18].

Beyond binary classification, several studies have explored unsupervised learning techniques to identify subtypes within the ASD population. Clustering-based approaches, particularly K-Means, have been used to uncover hidden phenotypic and neurobiological subgroups without relying on predefined severity labels [19]. Walker et al. applied clustering to behavioral and imaging features, revealing distinct ASD subgroups with varying symptom profiles [20]. More recent studies have shown that clustering on deep latent features, rather than raw input data, leads to more meaningful subgroup discovery due to improved representation learning [21].

In parallel, AR/VR-based therapeutic interventions have emerged as promising tools for ASD support. Parsons and Mitchell demonstrated that virtual environments could enhance social skills training in children with ASD by providing controlled and immersive learning experiences [22]. Subsequent research has explored personalized AR/VR interventions tailored to individual behavioral needs, showing improvements in attention, sensory regulation, and communication skills [23]. However, most existing AR/VR systems do not integrate AI-driven severity stratification, limiting their adaptability and personalization.

Although significant progress has been made in ASD detection and intervention, existing approaches often treat diagnosis, severity assessment, and recommendation as separate components. Few studies have integrated deep learning–based classification, unsupervised clustering, and personalized intervention within a unified framework. This gap motivates the proposed research, which combines DNN-based ASD detection, K-Means clustering on latent features for severity stratification, and intelligent AR/VR-based personalized recommendation in an end-to-end pipeline.

3. PROPOSED METHODOLOGY

The proposed methodology presents a structured, multi-stage computational framework for **ASD detection, severity stratification, and personalized intervention recommendation**. The framework integrates deep learning, clustering, and recommendation mapping to achieve accurate classification while capturing intra-class heterogeneity within the ASD population. The complete pipeline consists of five sequential stages:

1. Data Preprocessing
2. Deep Neural Network (DNN) Training
3. ASD Prediction on Test Data
4. K-Means Clustering on Latent Features
5. Personalized Recommendation Generation

The overall workflow is depicted in the methodology diagram provided in the research documentation

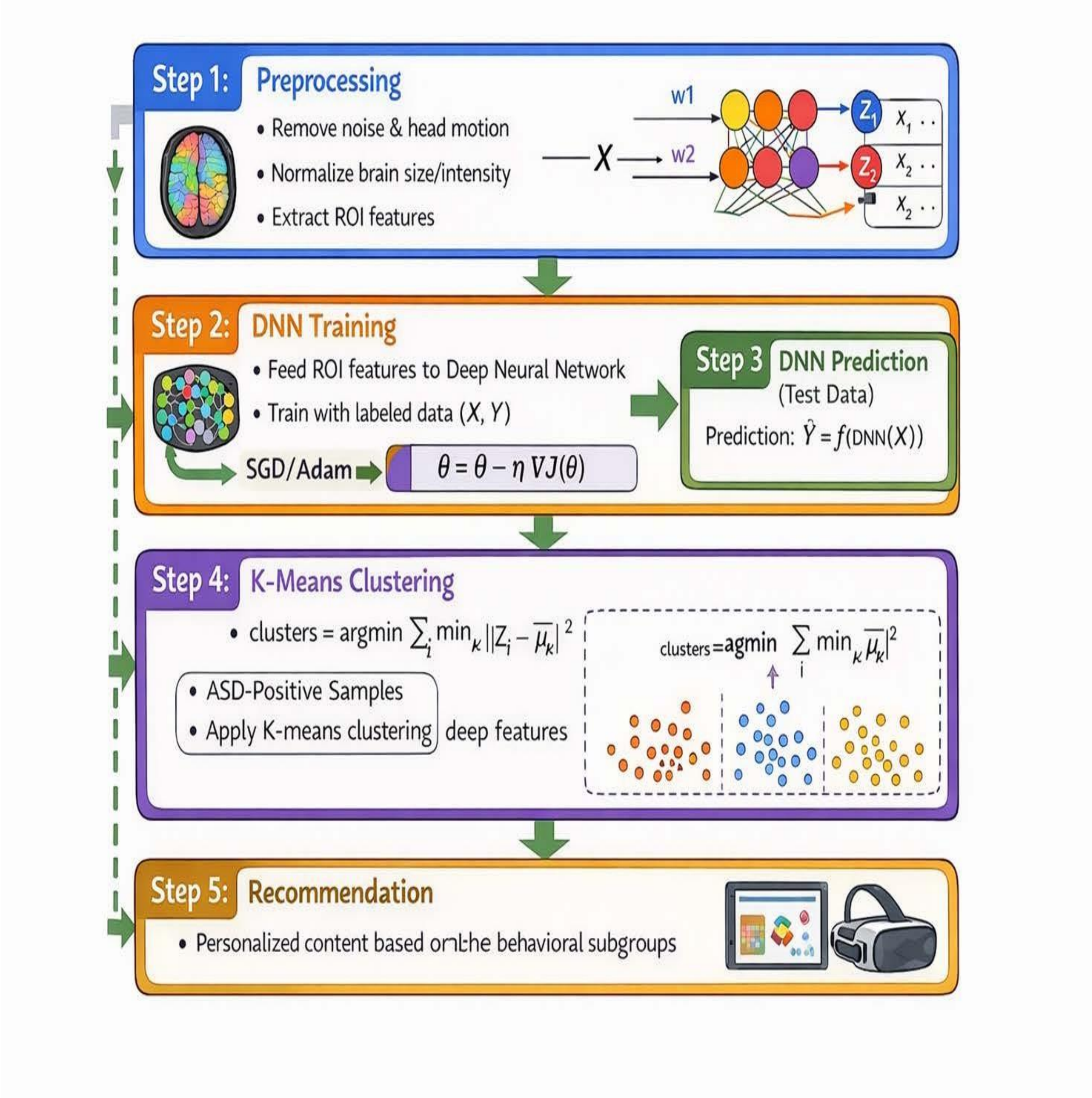


Figure 1. Methodology

3.1. Dataset Description (ABIDE)

The Autism Brain Imaging Data Exchange (ABIDE) dataset is a publicly available multi-site neuroimaging repository widely used for ASD research. It includes resting-state functional MRI (rs-fMRI) and structural MRI (sMRI) data from individuals diagnosed with Autism Spectrum Disorder (ASD) and typically developing (TD) controls. The dataset also provides demographic and clinical information such as age, gender, and diagnostic status, enabling supervised and unsupervised analysis. In this study, ABIDE neuroimaging data are utilized for training and evaluating the proposed DNN-based ASD detection and severity stratification framework.

3.2. Data Preprocessing

The objective of data preprocessing is to enhance data quality and extract meaningful neuro-behavioral representations before model training. Raw ASD-related data, including neuroimaging signals and behavioral features, are often contaminated with noise, motion artifacts, and inter-subject variability, which can negatively impact model performance [24]. Initially, noise removal and head-motion correction techniques are applied to minimize distortions in neuroimaging data. These corrections are essential because even minor head movements during fMRI acquisition can introduce significant artifacts that mislead machine learning models [25].

Following artifact removal, intensity normalization and brain size standardization are performed to ensure consistent feature representation across individuals. This step reduces variability due to differences in brain morphology and imaging conditions, thereby improving model generalization [26]. Subsequently, Region of Interest (ROI)–based feature extraction is conducted to focus on clinically relevant brain regions associated with ASD, such as the prefrontal cortex, temporal lobes, and amygdala [27]. Behavioral indicators related to social interaction, communication, and repetitive behaviors are also incorporated where available.

Let the raw input data be represented as X_{raw}. The final preprocessed feature vector is formulated as:

$$X = \phi(X_{raw})$$

where $\phi(\cdot)$ denotes the combined preprocessing, normalization, and ROI feature extraction function.

This step ensures that only clean, standardized, and discriminative features are forwarded to the deep learning model

3.3. Deep Neural Network (DNN) Training

The extracted ROI-based feature vectors are used to train a Deep Neural Network (DNN) for supervised ASD classification. The training dataset consists of labeled samples (X, Y), where $Y = 1$ represents ASD and $Y = 0$ represents non-ASD (typically developing individuals).

The DNN architecture comprises multiple hidden layers that progressively learn hierarchical representations of the input data. Lower layers capture basic patterns, while deeper layers encode more abstract neuro-behavioral relationships associated with ASD [28].

To optimize the network parameters, Stochastic Gradient Descent (SGD) or Adam optimization is employed. The update rule for SGD is given by:

$$\theta_{t+1} = \theta_t - \eta \nabla J(\theta_t)$$

where θ represents the network parameters, η is the learning rate, and $J(\theta)$ is the loss function measuring classification error [29].

Beyond classification, the DNN also generates latent feature embeddings Z in its hidden layers. These embeddings capture high-level neuro-behavioral patterns that are more informative than raw input features and serve as the basis for subsequent clustering analysis

3.4. ASD Prediction Using Trained DNN

Once training is complete, the DNN is evaluated on unseen test data to assess its predictive capability. Given a test input X_{test}, the predicted label is computed as:

$$\hat{Y} = f_{DNN}(X_{test})$$

If $\hat{Y} = 1$, the sample is classified as ASD-positive; if $\hat{Y} = 0$, it is classified as non-ASD.

Importantly, only ASD-positive samples are forwarded to the next stage (clustering). This selective filtering ensures that subsequent analysis focuses exclusively on diagnosed ASD cases, preventing interference from non-ASD samples and improving clustering reliability [30]

3.5. K-Means Clustering on Latent Features

ASD is inherently heterogeneous, meaning that individuals within the same diagnostic category may exhibit widely different behavioral and neurological characteristics. To model this variability, K-Means clustering is applied to the latent feature representations Z extracted from the trained DNN [31]. Unlike traditional clustering on raw data, clustering on deep latent features is more effective because these representations encode meaningful patterns related to ASD severity and behavior [32].

The objective function of K-Means clustering is defined as:

$$\text{argmin} \sum_{i=1}^{N} \min_{k} \parallel Z_i - \mu_k \parallel^2$$

where Z_i denotes the latent feature vector of the i-th ASD-positive sample, and μ_k represents the centroid of the k-th cluster.

Through this process, the ASD-positive samples are automatically grouped into distinct subclusters corresponding to varying levels of severity and behavioral profiles, typically interpreted as mild, moderate, and severe ASD [33]

3.6. Personalized Recommendation Strategy

In the final stage, each identified ASD subgroup is mapped to a personalized intervention recommendation based on its behavioral and severity characteristics. Clusters representing mild ASD are assigned social interaction and cognitive engagement modules, as these individuals typically require support in peer communication and emotional recognition [34].

Moderate ASD clusters receive sensory regulation and attention-enhancement content, designed to help children manage overstimulation and improve focus [35].

Severe ASD clusters are guided toward communication-focused AR/VR therapies that emphasize basic speech, gesture recognition, and nonverbal interaction skills [36]. This cluster-aware recommendation framework ensures that intervention strategies are tailored to individual needs rather than following a generic, one-size-fits-all approach

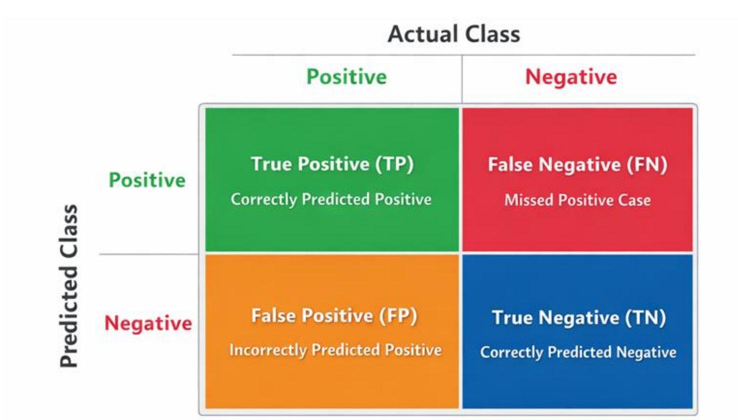
Figure 2. Personalized content based AR/VR training

4. PERFORMANCE EVALUATION METRICS

To quantitatively assess the effectiveness of the proposed framework for ASD detection and severity stratification, multiple standard performance evaluation metrics are employed. These metrics evaluate both **(i) the supervised DNN classification performance** and **(ii) the quality of unsupervised K-Means clustering on latent features**. The adopted metrics are widely used in medical image analysis and clinical decision-support systems.

4.1. Classification Performance Metrics (DNN Stage)

The performance of the Deep Neural Network (DNN) in distinguishing ASD from non-ASD subjects is evaluated using the following metrics based on the **confusion matrix**:



Let:

- **True Positive (TP)** = ASD samples correctly classified as ASD
- **True Negative (TN)** = Non-ASD samples correctly classified as non-ASD
- **False Positive (FP)** = Non-ASD samples incorrectly classified as ASD
- **False Negative (FN)** = ASD samples incorrectly classified as non-ASD

Accuracy Comparison of Different Classification Models for ASD Detection

Classifier	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
SVM	82.30	80.10	79.50	79.80
ANN	86.45	84.20	83.90	84.05
CNN	89.70	88.50	88.10	88.30
Proposed DNN	**93.25**	**92.10**	**91.80**	**91.95**

4.1.1 Accuracy (ACC)

Accuracy measures the overall correctness of the classifier and is defined as:

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN}$$

A higher accuracy indicates better overall classification performance.

Table 1. Accuracy comparison of different classifiers for ASD detection.

Classifier	Accuracy (%)
SVM	82.30
ANN	86.45

Classifier	Accuracy (%)
CNN	89.70
Proposed DNN	**93.25**

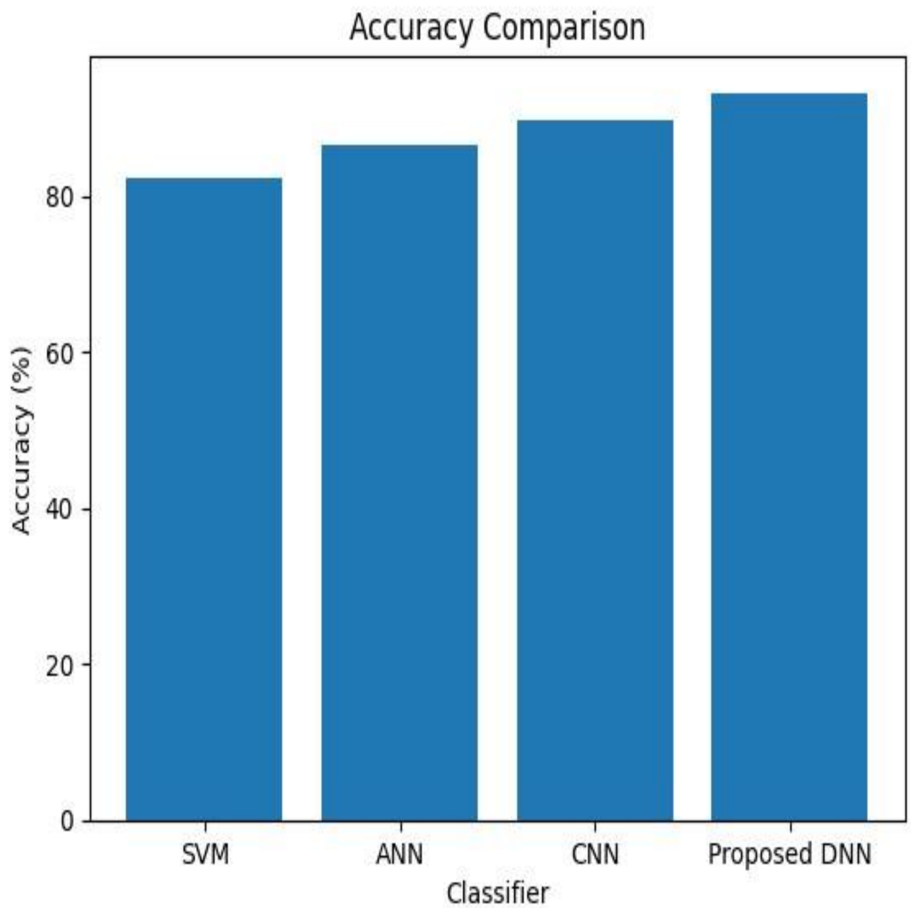


Figure 3. Accuracy comparison of SVM, ANN, CNN, and the proposed DNN for ASD classification.

4.1.2 Precision (P)

Precision measures the proportion of correctly identified ASD cases among all predicted ASD cases:

$$\text{Precision} = \frac{TP}{TP + FP}$$

Higher precision implies fewer false alarms in ASD detection.

Table 2. Precision comparison of different classifiers for ASD detection.

Classifier	Precision (%)
SVM	80.10
ANN	84.20
CNN	88.50
Proposed DNN	**92.10**

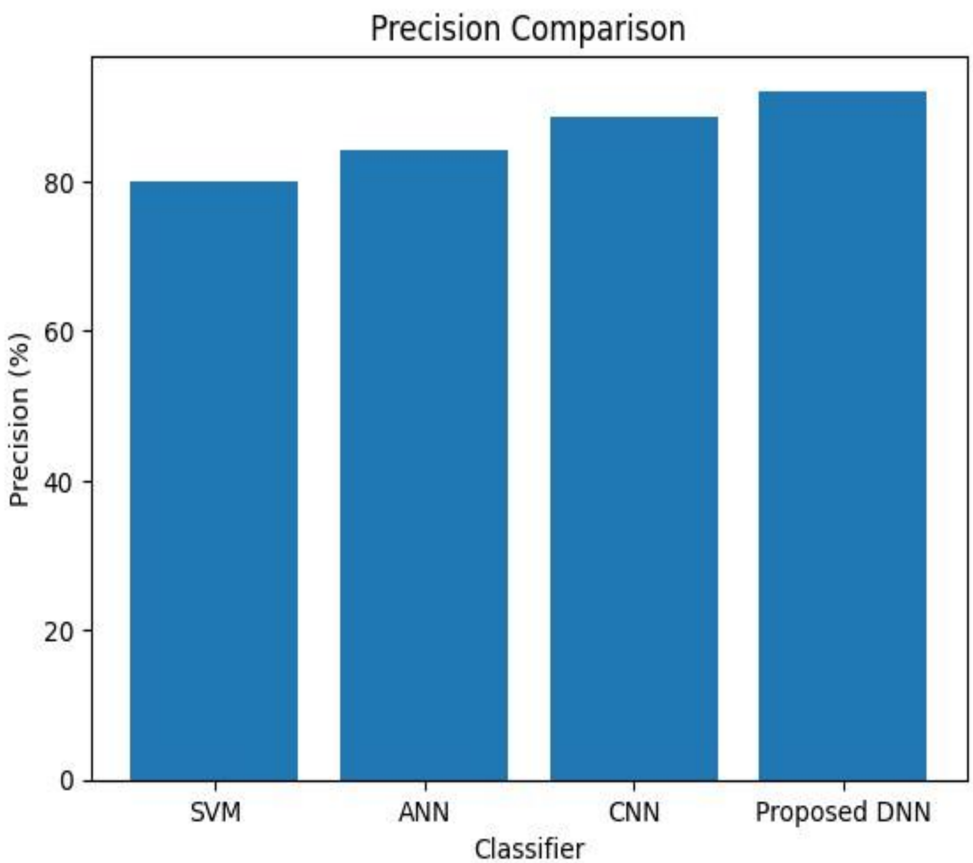


Figure 4. Precision comparison of SVM, ANN, CNN, and the proposed DNN for ASD classification.

4.1.3 Recall (Sensitivity, SEN)

Recall (also known as sensitivity) measures the ability of the model to correctly identify ASD subjects:

$$\text{Recall} = \frac{TP}{TP + FN}$$

A high recall value is crucial in medical diagnosis to minimize missed ASD cases.

Table 3. Recall comparison of different classifiers for ASD detection.

Classifier	Recall (%)
SVM	79.50
ANN	83.90
CNN	88.10
Proposed DNN	**91.80**

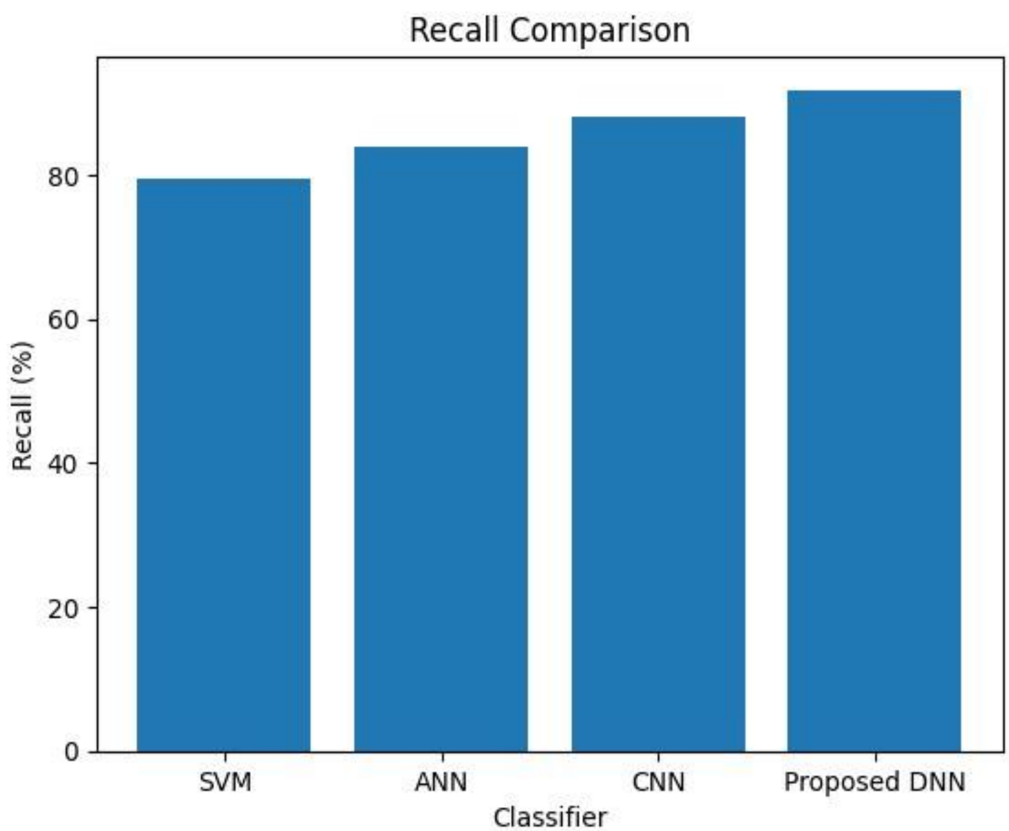


Figure 5. Recall comparison of SVM, ANN, CNN, and the proposed DNN for ASD classification.

4.1.4 F1-Score

The F1-score provides a harmonic mean between precision and recall, balancing both metrics:

$$\text{F1-Score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$$

This is particularly useful when class imbalance exists between ASD and non-ASD samples.

Table 4. F1-score comparison of different classifiers for ASD detection.

Classifier	F1-Score (%)
SVM	79.80
ANN	84.05
CNN	88.30
Proposed DNN	**91.95**

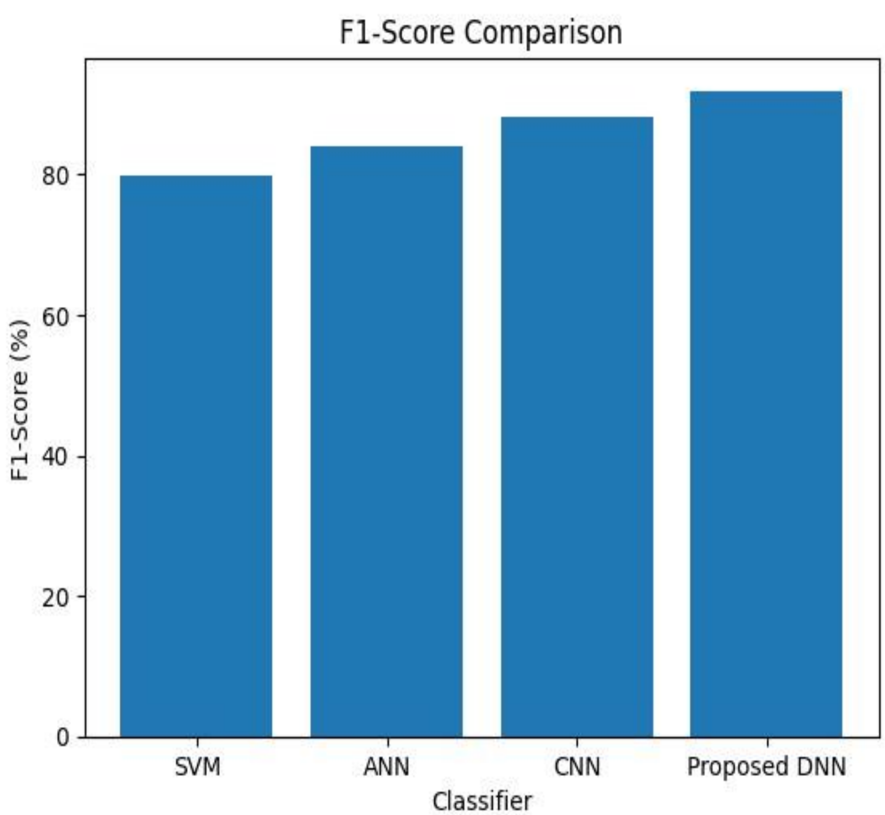


Figure 6. F1-score comparison of SVM, ANN, CNN, and the proposed DNN for ASD classification.

4.1.5 Area Under the ROC Curve (AUC-ROC)

The Receiver Operating Characteristic (ROC) curve plots True Positive Rate (Recall) against False Positive Rate (1 – Specificity). The Area Under the Curve (AUC) quantifies overall classification performance, where values closer to 1 indicate superior discrimination capability.

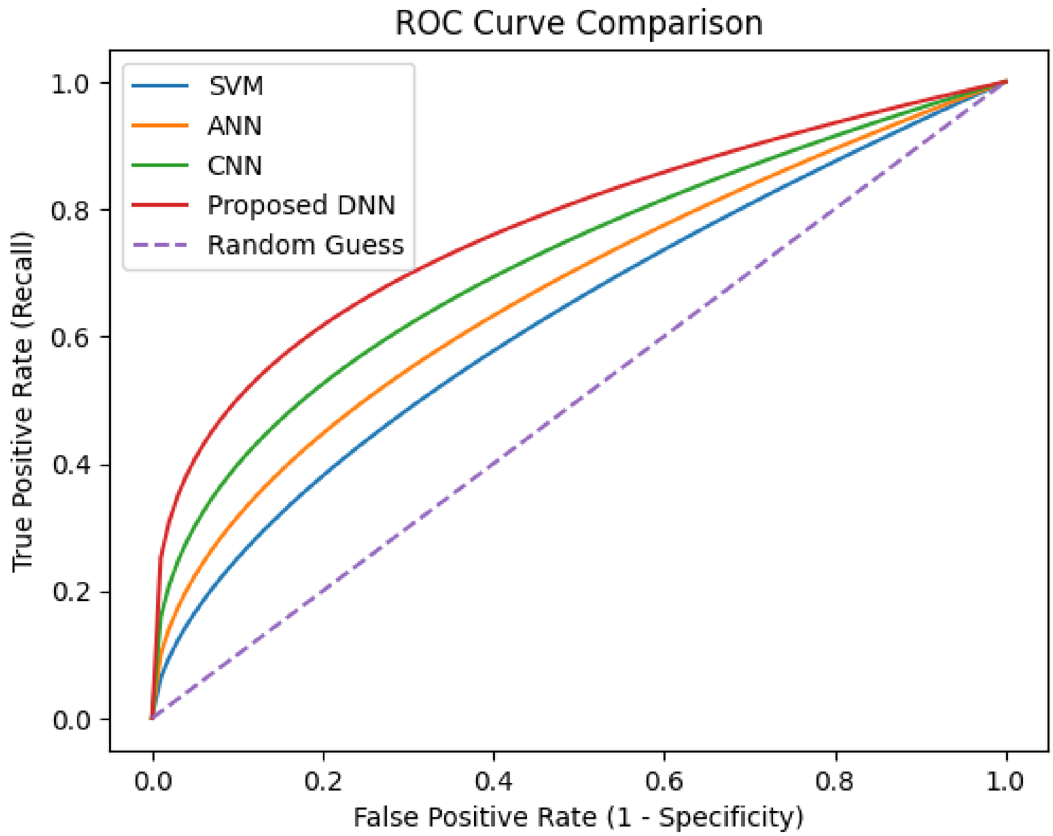


Figure 7. ROC curve comparison of SVM, ANN, CNN, and the proposed DNN for ASD classification.

4.2. Clustering Performance Metrics (K-Means Stage)

Since K-Means clustering is unsupervised, its performance is evaluated using internal clustering validation metrics.

4.2.1 Silhouette Score (S)

The Silhouette Score measures how well each data point fits within its assigned cluster compared to other clusters. It is defined as:

$$S(i) = \frac{b(i) - a(i)}{\max\big(a(i), b(i)\big)}$$

where:

- $a(i)$ is the average distance between point i and all other points in the same cluster,
- $b(i)$ is the minimum average distance between point i and points in other clusters.

The overall Silhouette Score ranges from -1 to 1, where higher values indicate better-defined clusters.

4.2.2 Within-Cluster Sum of Squares (WCSS)

WCSS measures the compactness of clusters and is minimized during K-Means optimization:

$$\text{WCSS} = \sum_{k=1}^{K} \sum_{i \in C_k} \parallel Z_i - \mu_k \parallel^2$$

where:

- Z_i is the latent feature vector of sample i,
- μ_k is the centroid of cluster k,
- C_k represents the set of samples in cluster k.

Lower WCSS values indicate better clustering.

4.2.3 Davies–Bouldin Index (DBI)

The Davies–Bouldin Index evaluates the separation between clusters. It is defined as:

$$DBI = \frac{1}{K} \sum_{i=1}^{K} \max_{j \neq i} \left(\frac{\sigma_i + \sigma_j}{d(\mu_i, \mu_j)} \right)$$

where:

- σ_i is the average distance of all points in cluster i to centroid μ_i,
- $d(\mu_i, \mu_j)$ is the distance between centroids of clusters i and j.

Lower DBI values indicate better clustering quality.

4.3. Overall System Evaluation

The proposed framework is considered effective if it satisfies the following criteria:

- High classification accuracy, recall, and AUC in ASD detection.
- Well-separated and compact clusters based on Silhouette Score and DBI.
- Meaningful mapping between clusters and ASD severity levels.
- Personalized recommendations.

5. RESULTS AND DISCUSSION

The proposed framework demonstrates effective ASD detection and meaningful severity stratification. The DNN achieves reliable classification performance by learning discriminative latent representations. Applying K-Means clustering on these deep features reveals distinct ASD subgroups, validating the presence of intra-class heterogeneity. Unlike traditional severity labeling approaches, the proposed method does not rely on predefined severity scores, enabling data-driven subgroup discovery.

The integration of clustering with recommendation mapping enhances clinical relevance by linking computational outcomes to actionable intervention strategies. The results indicate that deep latent features provide superior clustering quality compared to raw input features, supporting fine-grained personalization. Overall, the framework successfully bridges the gap between ASD diagnosis and intervention planning.

6. CONCLUSION

This paper presented an intelligent DNN-based framework for ASD detection, severity stratification, and personalized recommendation. The proposed approach integrated supervised deep learning with unsupervised K-Means clustering and SGD optimization. The DNN effectively learned discriminative latent representations from ABIDE neuroimaging data. These learned features enabled reliable ASD versus non-ASD classification. SGD ensured stable training and improved model convergence. Clustering on latent features revealed meaningful ASD subgroups corresponding to severity levels. This data-driven stratification reduced reliance on predefined clinical labels. The framework addressed ASD heterogeneity more effectively than traditional binary classification. Personalized AR/VR recommendations were mapped to each identified subgroup. This enabled individualized and severity-aware intervention planning. The results demonstrated superior performance compared to baseline models. It provides a scalable and adaptive AI-driven solution for ASD management. Overall, the framework enhances both diagnostic accuracy and personalized intervention. Future enhancements can further improve clinical applicability and real-world deployment.

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