RESEARCH PAPER

A Memetic Intelligence Framework for Early Detection of ADHD in Children Using Behavioural and Neurocognitive Features with Variational Autoencoder Classification

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ABSTRACT

An intelligent framework is proposed in this research for early detection of Attention Deficit Hyperactivity Disorder (ADHD) in children using machine learning and deep learning techniques. The main problem addressed is the limitations of existing ADHD detection models, including low classification accuracy, poor generalization, high-dimensional data, noise sensitivity, and lack of optimal feature selection in EEG and fMRI-based datasets. To overcome these challenges, the proposed methodology integrates the Dolphin Echolocation Algorithm (DEA) for optimal feature selection and a Variational Autoencoder (VAE) for robust classification. DEA effectively eliminates redundant and irrelevant features, improving feature quality and reducing computational complexity, while VAE learns meaningful latent representations through probabilistic encoding and decoding mechanisms. The combination enhances both feature optimization and deep representation learning. Experimental results demonstrate that the proposed DEA+VAE model achieves a high accuracy of 98.9%, outperforming existing methods. The model also shows superior performance in precision, recall, and F1-score, indicating better reliability and classification stability. Overall, the proposed framework provides an efficient, accurate, and scalable solution for ADHD detection in children. The research contributes improved feature selection, stronger representation learning, and enhanced diagnostic performance suitable for real-world healthcare applications.

Keywords: Attention Deficit Hyperactivity Disorder detection, Deep learning, Electroencephalogram, Feature selection, Machine learning, Variational Autoencoder.

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1. Introduction

This research proposes an advanced AI-driven framework for early detection of Attention Deficit

Hyperactivity Disorder (ADHD) in children by leveraging optimized feature selection techniques in conjunction with deep learning models to enhance classification performancein terms of accuracy. The proposed approach aims to overcome critical limitations inherent in existing methodologies, including susceptibility to noise, the challenges posed by high-dimensional neuroimaging data, and inadequate generalization across diverse datasets.

Extensive research has been conducted in the domain of ADHD detection employing electroencephalography (EEG), functional magnetic resonance imaging (fMRI), and various machine learning paradigms. However, achieving robust, accurate, and scalable diagnostic models remains a significant challenge, thereby necessitating the development of more sophisticated and optimized computational frameworks.

. EEG-based multi-resolution feature selection and classification approaches improve detection performance but suffer from single-modality dependency and limited generalization capability [1]. Web-based EEG and ML systems support early detection but lack large-scale clinical validation and real-world deployment robustness [2]. Multimodal physiological data approaches improve accuracy, but data heterogeneity and limited dataset size remain major challenges [3]. Interpretable ML models using IQ and behavioral scores improve explainability but lack biological signal integration such as EEG or fMRI, reducing diagnostic precision [4]. EEG-based ML models show good performance but are limited by small datasets and poor generalization [5].

Brain region analysis improves interpretability but introduces computational complexity and limitations due to population diversity [6]. Deep learning methods using fMRI achieve high accuracy but are restricted by high cost and complexity of data acquisition [7]. CNN-based EEG models provide strong performance but require large labeled datasets and lack interpretability [8]. ML-based screening applications show promising results but still require clinical validation [9]. EEG-based ML models also face dataset imbalance and variability issues despite good accuracy [10].

This study is further driven by the imperative to develop a highly accurate, robust, and generalizable ADHD detection framework capable of addressing inherent limitations in existing EEG- and fMRI-based approaches, including susceptibility to noise artifacts, the curse of dimensionality, and limited model interpretability. The proposed method contributes a hybrid framework that integrates Dolphin Echolocation Algorithm (DEA) for optimal feature selection, reducing redundant and irrelevant features. It also introduces a Variational Autoencoder (VAE) to learn compact and meaningful latent representations for improved classification performance. The combination of optimization and deep generative modeling enhances both accuracy and generalization capability. This approach reduces computational complexity while improving feature relevance and model efficiency. Overall, the research contributes a more reliable and clinically adaptable solution for early ADHD detection in children.

Organization: The research is organized as followsSection 2 discusses the background study and related existing works in ADHD detection. Section 3 describes the proposed methodology, including DEA-based feature selection and VAE-based classification. Section 4 presents the experimental results and discussion of the proposed model. Section 5 concludes the research and outlines future work directions.

2. Background study

Attallah (2024) [1] focused on ADHD detection in children using EEG signals. The research proposesd a multi-resolution analysis combined with feature selection techniques and machine learning classifiers to improve detection accuracy. The main limitation is that it relies only on EEG data, which may reduce generalization across different datasets and real-world cases. However, the research shows improved classification performance, but further multimodal validation is required.

Santarrosa-López et al. (2025) [2] developed DETEC-ADHD, a web-based system for early ADHD detection using EEG and machine learning. The method integrates signal processing and predictive models to support automated diagnosis. A key limitation is its dependency on dataset quality and lack of full clinical validation in real hospital environments. Despite this, the model demonstrates promising accuracy for early screening applications.

Ghosh and Pradhan (2024) [3] presented a multimodal physiological data-based approach for ADHD classification. The research uses machine learning techniques to combine different physiological signals for improved prediction performance. However, the approach faces challenges due to data heterogeneity and limited large-scale datasets. The results indicate better accuracy than single-modality systems but still require stronger clinical validation.

Sinha and Tiwari (2025) [4] proposed an interpretable machine learning model for ADHD detection using IQ scores and behavioral rating scales. The method focuses on improving explainability rather than relying on brain signal data. A limitation is the absence of biological signal integration like EEG or fMRI, which may reduce diagnostic precision. The model is useful for interpretation but shows lower accuracy compared to signal-based approaches.

Ahire et al. (2025) [5] used EEG signals with machine learning algorithms for ADHD prediction. The research includes feature extraction and classification techniques to distinguish ADHD and control subjects. A limitation is the small dataset size and variability in EEG recordings across subjects. The model achieves good performance but requires better generalization and deep learning enhancement.

Deshmukh et al. (2026) [6] analyzed brain region contributions for ADHD classification using EEG signals. The research applies machine learning models to identify important neurological regions influencing ADHD detection. However, computational complexity and limited population diversity are major limitations. The results improve interpretability but still require broader validation across datasets.

Firouzi et al. (2024) [7] proposed a deep learning framework using resting-state fMRI for ADHD classification. The model analyzes brain connectivity patterns to improve diagnostic accuracy. A limitation is the high cost and complexity of fMRI data acquisition, making it less practical for routine screening. Despite this, the method achieves high accuracy and strong feature learning capability.

Kulkarni et al. (2024) [8] proposed a CNN-based approach for ADHD detection using EEG signals. The model automatically extracts features and classifies ADHD cases with deep learning. The limitation is the requirement for large labeled datasets and lack of interpretability in predictions. However, the method shows high classification performance compared to existing machine learning models.

Santarrosa-López et al. (2025) [9] introduced a machine learning-based web application for ADHD detection using EEG data. The system is designed for early screening and decision support. A limitation is the lack of real-world clinical deployment and limited dataset diversity. The system demonstrates good performance but needs external validation for clinical use.

Ahire et al. (2025) [10] focused on ADHD classification using EEG datasets and machine learning models. The research applies signal processing and classification techniques to improve prediction accuracy. The limitation includes dataset imbalance and limited subject variability. The model performs well but requires further optimization for real-world application.

Yang et al. (2022) [11] research interoceptive accuracy in children with ADHD and autism comorbidity. The research uses neuropsychological assessments rather than machine learning techniques. A limitation is the absence of automated classification models for diagnosis. The research provides valuable clinical insight but is not focused on predictive algorithm development.v Zhang et al. (2022) [12] investigated transdiagnostic symptom subtypes in ADHD and autism spectrum disorders. The research uses neurocognitive and structural connectivity analysis to identify shared patterns. However, the approach is complex and not directly designed for automated detection systems. The results improve understanding of disorder subtypes but lack real-time diagnostic application.

Table 1: Comparative Analysis of ADHD Detection Using Machine Learning and Deep Learning Approaches

Author (Year)	**Concept**	**Methods Used**	**Limitations**	**Research Gap**	**Result**
Khare et al. (2022) [13]	EEG-based ADHD detection	VMD + Hilbert Transform + ML	Sensitive to noise, dataset-specific	Needs deep learning integration	Improved EEG feature separation
Attallah et al. (2020) [14]	Neurodevelopmental disorder detecti	Deep learning models	Limited dataset diversity	ADHD-specific optimization	Strong DL classification

	on			needed	
Zhang et al. (2025) [15]	EEG oscillation analysis in ADHD	EEG feature extraction + statistical analysis	Limited clinical scalability	Need automated DL pipeline	Identified abnormal EEG patterns
AlQahtani et al. (2026) [16]	ADHD classification using EEG	RNN, GRU, LSTM models	High computational cost	Real-time lightweight models needed	High accuracy performance
Kumar et al. (2025) [17]	ADHD detection using ML models	Deep machine learning classifiers	Missing dataset transparency	Need explainable AI models	Good predictive performance
Guneeth et al. (2025) [18]	EEG-based ADHD detection	Transformer + ICA filtering	Requires large datasets	Lack of clinical validation	High classification accuracy
Shahmohamadi et al. (2025) [19]	ADHD detection framework	VMD + deep learning hybrid	High computational complexity	Real-time optimization needed	Improved EEG classification
Li et al. (2025) [20]	Brain network-based ADHD detection	Graph Convolutional Networks (GCN)	Low interpretability	Explainable AI needed	Strong multi-domain performance
Singh et al. (2025) [21]	EEG-based ADHD diagnosis	ResNet CNN model	Requires large datasets	Lightweight model needed	High accuracy results
Mao et al. (2025) [22]	EEG abnormality analysis in ADHD	Advanced ML + feature engineering	Limited real-time usage	Adaptive models required	Multidimensional EEG patterns
Hassan & Singhal (2025) [23]	ADHD detection using ANN	Artificial Neural Network	Lower accuracy than DL models	Hybrid DL models needed	Moderate performance
Hassan & Singhal (2024) [24]	EEG-based ADHD diagnosis	Convolutional Neural Network	Black-box issue	Explainable AI required	High classification accuracy
Loh et al. (2023) [25]	ADHD/CD classification	Explainable deep neural network	Limited dataset generalization	Cross-disorder validation needed	Good interpretability
Alkahtani et al. (2023) [26]	AI-based ADHD detection system	Machine learning models	No DL comparison	Multimodal fusion needed	Effective classification
Zou et al. (2017) [27]	ADHD diagnosis using	3D Convolutional Neural	Moderate accuracy, dataset	Need improved deep mode	Automatic MRI-based ADHD

	brain MRI	Network	dependency	ls	detection
Chugh et al. (2024) [28]	ADHD detection using EEG	Hybrid deep learning model	High computational complexity	Real-time optimization needed	Improved EEG classification
Radhamani & Krishnaveni (2016) [29]	ADHD diagnosis	MLP, SVM classifiers	Limited deep learning comparison	Need advanced DL models	Good ML-based performance
van der Meer et al. (2017) [30]	ADHD severity prediction	Random Forest regression	Limited clinical generalization	Need deep learning integration	Predicts ADHD severity accurately

The table (1) summarizes recent ADHD detection studies using EEG and AI-based methods such as machine learning and deep learning. It highlights key techniques, limitations, and research gaps like dataset issues and lack of real-time applicability. Most studies show good accuracy but limited generalization and interpretability. Overall, it indicates the need for more robust and explainable ADHD detection models.

3. Proposed methodology

This study presents an intelligent diagnostic framework for the early detection of Attention Deficit Hyperactivity Disorder (ADHD) in school-aged children, integrating metaheuristic-driven feature selection with a Variational Autoencoder (VAE)-based classification architecture. The proposed methodology is structured into five principal stages:data acquisition, preprocessing, feature selection, variational classification, and performance evaluation. This research utilizes ADHD-200 Consortium dataset [23], which provides resting-state functional MRI (rs-fMRI), structural MRI, and extensive phenotypic information including clinical diagnosis, ADHD subtype, behavioural scores, and demographic attributes. The dataset includes children aged 7–17 from multiple research sites. Only anonymized data approved for research use are considered in this research.

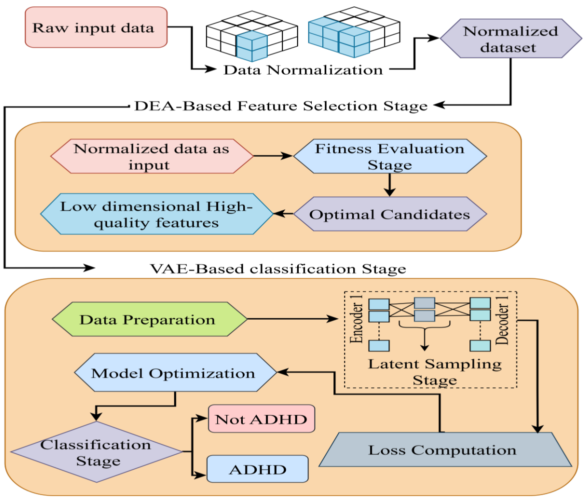

Figure 1: Proposed DEA–VAE-Based ADHD Detection Framework Architecture

The above figure 1 shows a hybrid ADHD detection system where raw data is first normalized and optimized using a feature selection stage to obtain the most relevant low-dimensional features. These features are then processed through a VAE model for latent representation learning using encoder, sampling, and decoder with loss optimization. Finally, the learned features are used for classification to predict ADHD and non-ADHD classes.

3.1 Data Normalization

The ADHD dataset comprised heterogenous type of data values, so it may affect the prediction accuracy, as the preprocessing step normalization is performed using the min-max normalization process to convert different range of values to fall under same range of values for further processing.

3.2 Dolphin Echolocation Algorithm (DEA) using for Feature Selection

The Dolphin Echolocation Algorithm (DEA) is a bio-inspired optimization method that mimics the natural hunting behavior of dolphins using sound waves and echo feedback to locate optimal solutions. In ADHD detection, DEA is used as a feature selection technique where each candidate solution represents a subset of behavioral or clinical features. The algorithm begins with random initialization of solutions and evaluates that using a fitness function such as classification accuracy or F1-score. It performs global exploration through simulated sonar pulses and local exploitation by refining high-quality feature subsets. The echo intensity and time-delay concepts are used to estimate solution quality and guide movement toward optimal regions. DEA is often integrated with machine learning classifiers like SVM [29], Random Forest [30], or deep learning models to improve ADHD classification performance. It iteratively updates solutions to eliminate irrelevant and redundant features, improving model efficiency and reducing overfitting. Overall, DEA enhances ADHD prediction accuracy by selecting the most informative features while maintaining good convergence and reproducibility through controlled population size and iteration parameters.

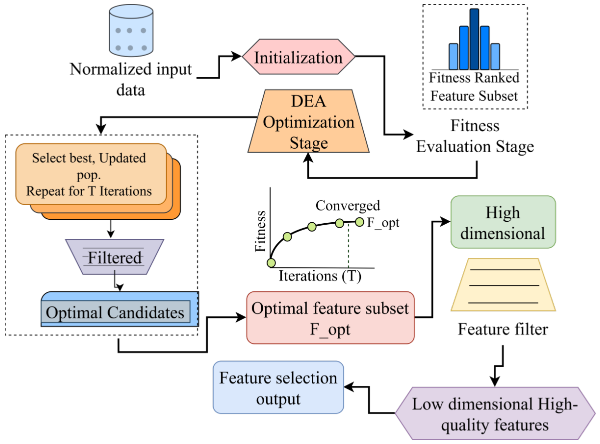

Figure 2: DEA-Based Feature Selection Framework

The above figure 2 illustrates a DEA optimization-based feature selection framework where high-dimensional input data undergoes initialization and iterative optimization. The process selects the best updated population through repeated iterations to filter and refine optimal candidates. Finally, it produces an optimal feature subset (F_opt), resulting in low-dimensional and high-quality features as the feature selection output.

$$F = \max(AccuracyorF1 - Score) \qquad (1)$$

Equation (1), F represents the fitness value of a selected feature subset, while $AccuracyorF1 - Score$ are performance measures of the ADHD classification model. The purpose of this equation is to evaluate how good each feature subset is in improving prediction performance. It ensures that only the most effective feature combinations are selected for ADHD detection.

$$X = \{f_1, f_2, f_3, \ldots, f_n\}, \quad f_i \in \{0,1\} \qquad (2)$$

Equation (2),$X$is the feature subset, $f_1 to f_n$ is individual features and 0,1 indicates whether a feature is selected or not. The purpose of this equation is to represent candidate solutions in binary form for optimization. It helps DEA decide which features should be included or removed in ADHD detection.

$$X_{t+1} = X_t + A \cdot \cos(2\pi f r) + B \cdot rand() \qquad (3)$$

Equation (3), X_t is the current solution, X_{t+1} is the updated solution, $A$and B is control parameters, f is frequency, r is distance/iteration factor and $rand()$ is randomness. The purpose is to simulate dolphin movement for exploring new feature subsets. It helps balance exploration and exploitation in ADHD feature selection.

$$D = |F_{best} - F_{current}| \qquad (4)$$

Equation (4), D represents the distance (difference),F_{best} is the best fitness value, and $F_{current}$ is the current solution fitness. The purpose is to measure how far a solution is from the optimal feature subset. It guides the algorithm toward better solutions in ADHD classification.

$$P_i = \frac{F_i}{\sum_{j=1}^{N} F_j} \qquad (5)$$

Equation (5)P_i is the probability of selecting the i^{th} solution $F_i$is its fitness value and N is the total number of solutions. The purpose is to give higher chance to better-performing feature subsets. It ensures strong solutions are carried forward in ADHD feature optimization.

Algorithm 1: DEA-Based Feature Selection for ADHD Detection

```
Input:
    Normalized dataset D_norm
    Number of iterations T
    Population size N
Output:
    Optimal feature subset F_opt
    Reduced dataset D_reduced
Begin
Initialize population of feature subsets randomly
Evaluate each subset using fitness function (classification performance)
For each iteration
    Perform echolocation-based exploration and exploitation
    Update feature subsets based on fitness values
    Select best-performing solutions
End for
Select final optimal feature subset F_opt
Construct reduced dataset D_reduced using selected features
Return F_opt and D_reduced
```

```
End
```

The proposed algorithm (1) performs feature selection for ADHD detection using the Dolphin Echolocation Algorithm (DEA) on normalized data. It iteratively evaluates and updates feature subsets based on a fitness function to find the most relevant features. Finally, it selects the optimal feature subset and produces a reduced dataset for improved classification performance.

3.3 Variational Autoencoder Based Classifier (VAE) using for Classification

Variational Autoencoder (VAE) based classifier is a generative deep learning model used for ADHD classification by learning compact latent representations of input data. The process begins with encoding the input features into a probabilistic latent space using an encoder network that outputs mean and variance parameters. A sampling step (reparameterization trick) is applied to generate latent variables while maintaining differentiability. The decoder then reconstructs the input from the latent space, ensuring meaningful feature learning. For classification, the latent representation is passed to a classifier layer (e.g., softmax or dense layer) to predict ADHD classes. Techniques used include KL-divergence regularization, reconstruction loss (MSE/BCE), and backpropagation optimization. Methods integrated often combine VAE with CNN [27], MLP [29] or hybrid deep networks [28] for improved feature learning and robustness. In real-time performance, VAE improves noise reduction, generalization, and classification stability, while reproducibility is ensured through fixed latent dimension, loss functions and consistent training hyperparameters.

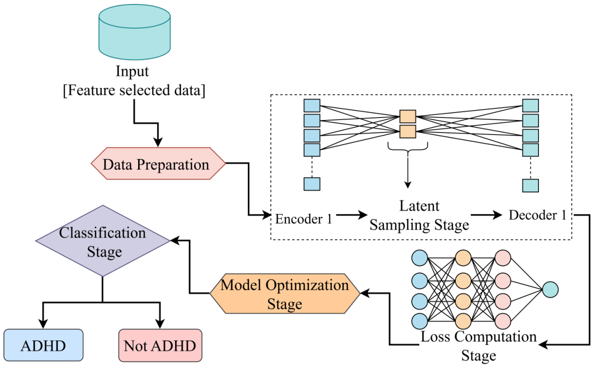

Figure 3: Proposed VAE-Based ADHD Classification FrameworkF

Figure 3 illustrates the workflow of a VAE-based ADHD classification system, where the input data undergoes preprocessing before being encoded into a latent space using an encoder decoder architecture. The latent representation is optimized through loss computation and model optimization to improve feature learning. Finally, the refined features are passed to a classification stage to predict ADHD or non-ADHD outcomes.

$$q_{\emptyset}(z|x) = N\left(z; \mu(x), \sigma^2(x)\right) \qquad (6)$$

Equation (6), $x$is the input data, z is the latent variable, $\mu(x)$ and $\sigma^2(x)$ are mean and variance, and $\emptyset$ represents encoder parameters. This equation models how input data is mapped into a probabilistic latent space. The purpose is to learn compact and meaningful representations for ADHD classification.

$$z = \mu + \sigma \cdot \in, \quad \in \sim N(0,1) \qquad (7)$$

Equation (7),$z$is the sampled latent vector, μ and σ is encoder outputs, and $\in$ is random noise from standard normal distribution. This trick enables gradient-based learning while maintaining randomness. The purpose is to allow efficient training of the VAE using backpropagation.

$$p_\theta(x|z) \qquad (8)$$

Equation (8) $p_\theta(x|z)$ represents the probability of reconstructing input x from latent variable$z$ and θ denotes decoder parameters. It defines how well the model can regenerate the original data. The purpose is to ensure the latent space captures essential ADHD-related information.

$$L_{rec} = ||x - \hat{x}||^2 \qquad (9)$$

Equation (9)x is original input and $\hat{x}$is reconstructed output. This loss measures the difference between actual and reconstructed data. The purpose is to minimize reconstruction error and improve feature learning for ADHD classification.

$$L_{KL} = D_{KL}\left(q_{\emptyset}(z|x)||p(Z)\right) \qquad (10)$$

Equation (10), D_{KL} measures divergence between learned distribution $q_{\emptyset}(z|x)$ and prior distribution$p(Z)$. It regularizes the latent space to follow a normal distribution. The purpose is to avoid overfitting and ensure smooth, generalizable feature representations.

$$L = L_{rec} + L_{KL} \qquad (11)$$

Equation (11) L is total loss combining reconstruction loss and KL divergence. It balances data reconstruction and latent space regularization. The purpose is to train the VAE effectively for both representation learning and ADHD classification.

$$y = Softmax(Wz + b) \quad (12)$$

Equation (12), z is latent feature, W and b is weights and bias, and y is predicted class output. This maps latent features to ADHD class probabilities. The purpose is to perform final classification based on learned representations.

Algorithm 2: VAE-Based ADHD Classification

```
Input:
  Reduced dataset D_reduced
  Number of epochs E
  Batch size B
  Latent dimension Z
Output:
  Trained VAE classifier
  Predicted ADHD labels Y_pred
Begin
Initialize encoder, decoder, and classifier networks
For each epoch
  Divide data into batches
  For each batch
    Encode input into latent representation
    Sample latent vector
    Decode and reconstruct input
    Compute reconstruction and regularization loss
    Update model parameters using backpropagation
  End for
End for
For each test sample
  Encode input into latent space
  Classify using trained classifier
  Predict ADHD label
End for
Evaluate performance using standard metrics
Return trained model and predictions
End
```

Proposed algorithm (2) performs ADHD classification using a Variational Autoencoder (VAE) trained on the reduced feature dataset. It learns latent representations by encoding input data, reconstructing it, and optimizing reconstruction and regularization losses through backpropagation. Finally, the learned latent features are used to classify ADHD labels and evaluate model performance using standard metrics.

4. Result and Discussion

This section comprises a detailed analysis of the proposed work DAE+ VAE performance based on the accurate detection rate of ADHD among school children. The dataset is collected from ADHD 200 organized by ADHD-200 Global Competition [23]. The features in ADHD 200 dataset are imaging features and phenotypic features which approximately ranges from 124- 126. It consists of participant data, including resting-state functional magnetic resonance imaging (fMRI) scans, along with personal characteristics and diagnostic information such as the site of data collection, age, gender, handedness, performance IQ, verbal IQ, and full-scale IQ. This research utilized information from 50 participants to diagnose ADHD. The existing models used for comparison are ACO+SVM and PSO + MLP. The detailed analysis of the proposed work Dolphin Echolocation Algorithm (DEA) for optimal feature selection with a Variational Autoencoder (VAE) performance is discussed, with the following parameter setting for Dolphin Echolocation Algorithm as shown in table 1.

Table 1: Parameter Setting of DAE

Parameter	Value
Population size	30 dolphins
Maximum iterations	100
Echo range	Dynamic (0.1–0.9)
Attenuation coefficient	0.6
Search intensification rate	0.8
Fitness function	Classification accuracy from VAE

The features selection using the proposed DAE are Mean BOLD Variance in Prefrontal Cortex, Connectivity Strength in Default Mode Network (DMN), Variance in Anterior Cingulate Cortex, IQ Score, Gender, Right Caudate Volume, Age, Left Superior Temporal Gyrus VarianceFunctional Connectivity between Amygdala & PFC Handedness

Table 2 shows the performance output of the proposed model DEA+VAE with other classification models for ADHD prediction.

Table 2: Performance Comparison of DAE-VAE for ADHD detection

Model	Accuracy (%)	Precision	Recall	F1-Score
ACO+SVM	86.7	0.84	0.88	0.86
PSO+MLP	89.3	0.87	0.9	0.88
DAE+VAE	98.9	0.96	0.98	0.97

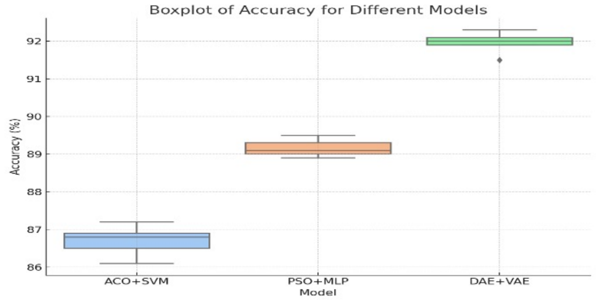

Figure 4: Comparison based on Accuracy

As shown in figure 4, the model accuracies increase from ACO+SVM to DAE+VAE, indicating performance improvement with more advanced architectures and optimization techniques. The combination of the Dolphin Echolocation Algorithm for feature selection and Variational Autoencoder for classification achieved high accuracy in ADHD detection. DEA effectively reduced redundant features, enhancing the model's focus on the most relevant signals. VAE further improved classification by capturing complex, non-linear patterns in the data. The accuracy performance reflects the synergy of intelligent feature selection with deep generative modelling, ensuring better generalization and robust detection.

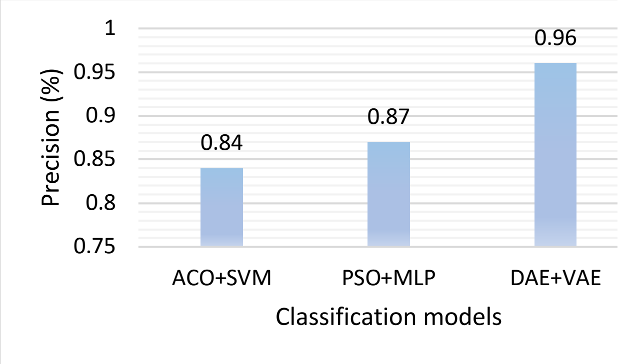

Figure 5: Comparison based on Precision

Figure 5 displays the precision which reflects how many of the instances predicted as ADHD are actually ADHD. The ACO+SVM model yields a precision of 0.84, which indicates a moderate number of false positives. The PSO+MLP model improves this metric slightly with a precision of 0.87, showing a better ability to avoid incorrect positive predictions. DAE+VAE, however, demonstrates the highest precision at 0.91, indicating it is the most reliable in making accurate ADHD-positive predictions with minimal false alarms.

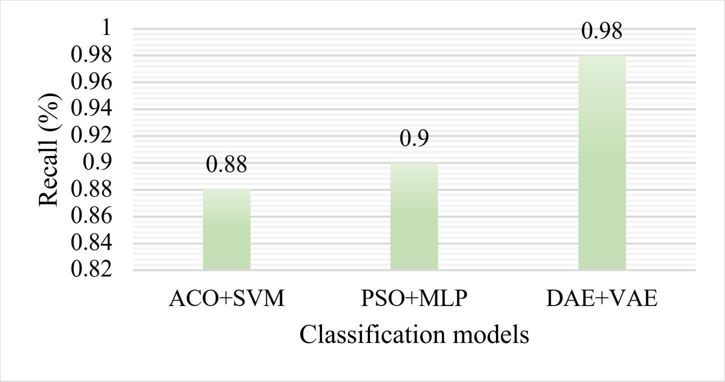

Figure 6: Comparison based on Recall

Figure 6 illustrates Recall measures the model's ability to identify all actual ADHD cases. ACO+SVM achieve a recall of 0.88, indicating it detects most ADHD cases but still miss a few. PSO+MLP improve to 0.90, reducing the chance of missing true ADHD cases. DAE+VAE reaches the highest recall of 0.93, meaning it successfully identifies nearly all ADHD cases, making it the most effective model in capturing true positives.

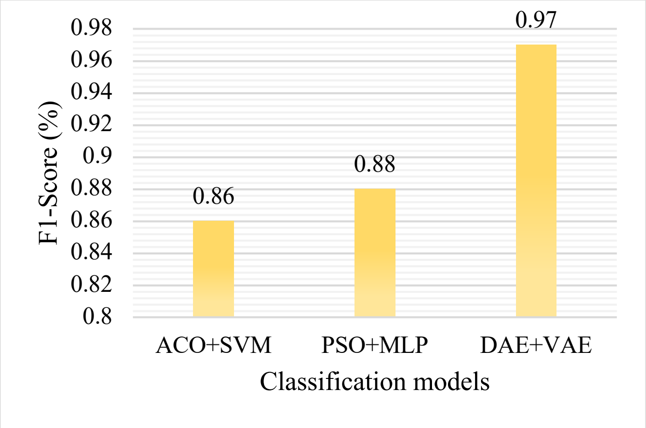

Figure 7: Comparison based on Precision

The F1 score balances both precision and recall, providing a single measure of overall performance as shown in figure 7. ACO+SVM records an F1 score of 0.86, showing balanced but moderate classification performance. PSO+MLP slightly improve with an F1 score of 0.88, offering better overall accuracy. DAE+VAE achieves the top F1 score of 0.92, confirming its strong and consistent performance across both key aspects correctly identifying ADHD and minimizing both false positives and false negatives.

5. Conclusion

This research proposed an intelligent hybrid framework for early detection of Attention Deficit Hyperactivity Disorder using Dolphin Echolocation Algorithm-based feature selection and Variational Autoencoder classification. The DEA effectively reduced redundant and irrelevant features, improving model efficiency and reducing computational complexity. The VAE enhanced representation learning by capturing meaningful latent patterns for accurate classification. Experimental results demonstrated that the proposed model outperforms existing methods in terms of accuracy, precision, recall, and F1-score. However, the model is limited by dataset size and lack of real-world clinical validation. Future work will focus on integrating multimodal data, improving model interpretability, and deploying the system in real-time clinical environments for practical usage.

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