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A Novel Fusion of Explainable Sparse Evoked Tiny Machine Learning Algorithms for an Effective Detection of Autism Spectrum Disorder Using IoT-Based EEG Signals

Kondalapuri Raajitha [a*], Dr. Sudha Thatimakula [b]

[a*] *Research Scholar, Department of Computer Science & Engineering, Sri Padmavati Mahila Visvavidyalayam, Tirupati, India. E-mail: raajithaprasadphd@gmail.com, Orcid: https://orcid.org/0009-0002-3319-5118*
[b] *Professor, Department of Computer Science & Engineering, Sri Padmavati Mahila Visvavidyalayam, Tirupati, India. E-mail: thatimakula_sudha@yahoo.com, Orcid: https://orcid.org/0000-0002-1943-9705*

Abstract

Autism Spectrum Disorder (ASD) is a complex neurological condition that typically shows up in early childhood. It affects how individuals interact with others and communicate. The impact can vary from person to person. Identifying it early and providing ongoing support can greatly improve outcomes. Electroencephalography (EEG) is used to study unusual brain activity and irregular neural patterns linked to ASD. Machine Learning (ML) and Deep Learning (DL) techniques have been applied to better predict and diagnose ASD, as well as support those living with it. However, these algorithms suffer from the computational overhead and non-interpretability black box problems, which limit the applicability for pervasive monitoring that aids in an early exploration of ASD patterns. To overcome this challenge, this research paper proposes a novel Internet of Things (IoT) based explainable sparse tiny ML algorithm, which has pipelined stages of pre-processing, sparse graphical feature extraction, model design and finally the deployment in resource-constrained devices. The performance of this new method is measured using accuracy, precision, recall, and F1-score, and it is compared with other existing methods. To assess how easy it is to understand, the study uses SHAP analysis. The results show that the proposed system has a high accuracy of 0.99, precision of 0.984, recall of 0.98, and F1-score of 0.99, along with efficient energy use on the hardware. It highlights the value of lightweight ML models and their ability to offer clear insights, which is important for creating better systems to understand and support individuals with ASD.

Keywords: Autism Spectrum Disorder, Tiny Machine Learning, Explainable Sparse, Internet of Things, Sparse Graphical Centrality, Electroencephalography.

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Introduction

ASD is a neurobiological disorder that environmental and genetic factors play a major role in developing the unforeseen abnormalities (Angulo-Ruiz et al., 2023; Tang et al., 2024). ASD is characterised by a wide range of social and behavioural communication in individuals. According to the World Health Organisation (WHO), 1 in 160 individuals are affected with ASD symptoms, which include intellectual disability or developmental co-ordination disorder, further complicating the diagnostic process. Hence, the early prediction of ASD is considered to be most significant for timely prevention and diagnosis outcomes (Xu et al., 2024). Delayed diagnosis, often caused by limited intelligent algorithms with complex evaluation strategies, can lead to high false rates during developmental stages.

Recent improvements in neuroimaging technologies, especially functional Magnetic Resonance Imaging (fMRI) and Computer Tomography (CT) scans, have offered valuable insights into the unique brain patterns associated with ASD (Kang et al., 2020). Both techniques are non-invasive and provide high spatial resolution, leading to more accurate diagnostic outcomes and becoming the preferred methods for studying brain connectivity in ASD (Hossain et al., 2021). Nonetheless, conventional diagnostic approaches for ASD depend largely on behavioural evaluations and clinical observations, which can be time-consuming and vary between different clinicians (Chung et al., 2024). In addition, Electroencephalography (EEG) signals are frequently used to analyse variations in brain activity, assisting clinicians in improving the diagnostic process (Ali et al., 2020; Zhu et al., 2024). Therefore, there is an increasing need for an innovative intelligent system based on EEG, which would enable the detection of autism spectrum disorder. Different hybrid approaches have been used to achieve efficient detection of ASD through brain pattern analysis.

Problem Structure

The implementation of EEG-based ASD detection systems on IoT devices is needed for long-term monitoring and personalised screening, making it specifically suitable for ASD prediction in its early stages of existence (Radhakrishnan et al., 2021; Lalawat & Bajaj, 2024). Despite its high-profile advantages, existing hybrid architectures suffer from computational complexity and overhead problems. This limits its applications to be deployed in the resource-constrained devices, especially Internet of Things (IoT) and Edge devices. Hence, an intelligent and scalable platform is needed for low-latency and accessible ASD monitoring beyond the conventional clinical settings.

Research Contribution

Due to the current limitations, this paper presents a novel explainable IoT-based sparse deep learning framework for detecting ASD levels using EEG signals. The proposed framework incorporates networks designed to accurately identify ASD through EEG data. The key contributions of this research are outlined as follows.

1) The present paper presents a new explainable framework that integrates a sparse graphical feature extraction procedure to improve the effectiveness and identification of ASD degrees, which is appropriate for implementation on resource-limited IoT devices.
2) A novel Spare Centrality feature is introduced to identify the important EEG channels, which are utilised to characterise abnormal neural patterns. These features represent the EEG dynamics, which are then utilised for implementing in the low-power IoT devices.
3) The suggested framework integrates the extracted sparse graph features with a lightweight Siamese Random Forests-based learning model, enabling efficient inference on IoT devices with limited memory, processing power, and energy resources.
4) The comprehensive experimentation has been conducted using the real-time EEG clinical datasets, and performance metrics are calculated, which are then compared with those of other learning models. Further, interoperability of the proposed framework was assessed with the help of SHAP to examine the feature significance that led to the model's clinical performance.

Paper Organisation

This paper is structured as follows: Section 2 provides a literature review of researches utilizing machine learning and deep learning techniques to create intelligent ASD detection systems. Section 3 covers the dataset acquisition method and proposed architecture methodology. Section 4 deals with experimental work, results analysis, and comparisons. Conclusion and future improvements are discussed in Section 5.

Related Works

A paper proposed a deep learning method to enhance seizure detection in wearable EEG devices using the CHB-MIT database. The study used Fully Convolutional Networks (FCN), 2D CNNs, and different types of LSTM models combined with SMOTE for data balancing. The FCN model achieved 92% accuracy but had a 33% recall for seizures. The 2D CNN model had higher accuracy at 96% and better seizure recall at 70%. The LSTM model with SMOTE performed the best, achieving 89% accuracy, 91% precision, 86% recall, and an F1-score of 0.89 (Alarfaj et al., 2025). Even though the model was well tested, the standard LSTM model showed poor performance with only 53% accuracy, showing how sensitive it is to imbalanced data without proper preprocessing.

In a study, the KANs were proposed as a replacement model for MLPs for the purpose of EEG seizure classification by highlighting the robustness of KANs in noisy conditions. In the experiment, two EEG datasets, namely the Bonn and CHB-MIT, were used under varying conditions of network configuration and multiplicative noise. KANs were found to be more stable compared to MLPs, especially in small networks, based on different evaluation criteria. Nonetheless, there were limitations when dealing with larger networks (Allogmani, 2025).

Another similar study developed ML models that combined careful data preprocessing with explainable AI techniques for paediatric ASD diagnosis. The methodological approaches were used to eliminate outliers, handle missing values, and conduct feature selection using clinically based knowledge. The process was tested through 10-fold cross-validation and grid search methods to optimise hyperparameters in R using the CARET package. Neural networks and extreme gradient boosting were determined to perform better compared to other approaches, with XAI highlighting behavioural variables. A key limitation is that the study primarily relied on behavioural features, which might not fully capture deep neurological patterns, thus affecting the method's clinical reliability (Jeon et al., 2024).

A research study proposed a combination of handcrafted feature selection with a cascade deep maxout fuzzy hybrid approach for ASD detection (Singh & Kakkar, 2024). Fuzzy methods were employed to handle the uneven EEG patterns for effective ASD brain activities. The paper's results showed a classification accuracy of 0.930, which provides effectiveness for EEG-based ASD detection. The approach is limited to offline processing and cannot be suitable for online or real-time applications (Singh & Kakkar, 2024).

A similar paper proposed an energy-efficient wearable EEG sensor for detecting ASD at an early stage. To prove its hardware proficiency, hardware-dependent embedded machine learning approaches are directly deployed in the embedded devices for continuous monitoring of ASD among the children. The framework incorporates the multi-scale entropy extraction and Welch's power spectrum to extract the spatial and temporal features that enhance the performance of the classifier to 96% with the reduced energy consumption by 97%, providing a sustainable tool for diagnosing the neurodevelopmental disease in a real-time environment (Alhassan et al., 2023).

A paper proposes the EEG -Based Autism Detection System using multi-input 1D Convolutional Neural Networks, where each EEG channel serves as an individual set of inputs processed by the multiple concatenation layers. That model demonstrated the efficacy of the model by achieving an accuracy of 99.16% and outperforms the traditional variants of convolutional layers (Peya et al., 2022). Though the method provides a highly accurate and standardised tool for potential ASD diagnosis, it suffers from high computational complexity and overhead.

Another proposed model used an innovative Internet of Medical Things (IoMT) based ASD detection system using the EEG signals. The framework introduces the Channel and Spatial attention networks for the high-level feature extraction process and a modified fish swarm algorithm for optimal feature selection with the Hinging Hyperplane Neural networks for the final classification process. The suggested framework has achieved the remarkable performance over the existing algorithms by reaching an accuracy of 99.95%. It gave a highly reliable and scalable diagnostic decision for the support system to use in real-world clinical and portable monitoring systems (Mittal et al., 2024).

Another study developed a time-frequency spectrogram-based framework for automatic ASD identification from EEG signals. This methodology employed Short-Time Fourier Transform to convert EEG signals that are already pre-processed into 2D spectrogram images, followed by parallel evaluation using machine learning (with PCA feature selection) and deep learning models. The research showed improved efficiency using deep learning compared to machine learning techniques, performing better than any current systems. Nevertheless, the proposed technique faces certain limitations concerning the high computational complexity and time-consuming preprocessing procedures (Temiz et al., 2025).

This paper focuses on the problem of computational complexities and the lack of interpretability associated with previous research in using EEGs to diagnose ASD. Previous studies demonstrated that machine learning algorithms have been successful in diagnosing ASD. However, those models have failed to overcome the problems related to computational complexity and have been unable to scale to real-life implementation owing to the huge demand for computational power required. This proposed model offers a breakthrough in solving these problems, offering a scalable method that is also highly accurate and interpretable using the SHAP algorithm to provide explanations of decisions.

Systematic EEG-based ASD Prediction

In this section, an IoT-based explainable sparse graph framework is proposed. The framework consists of five components: 1) EEG pre-processing using bandpass filters, 2) Decomposition of pre-processed EEG waveforms using discrete wavelet transforms (DWT), 3) Graphical Sparse Centrality Feature extraction, 4) Tiny ML Model design, 5) Deployment Process, 6) Interpretability Analysis. The detailed description of each component in the suggested framework is provided in the preceding section.

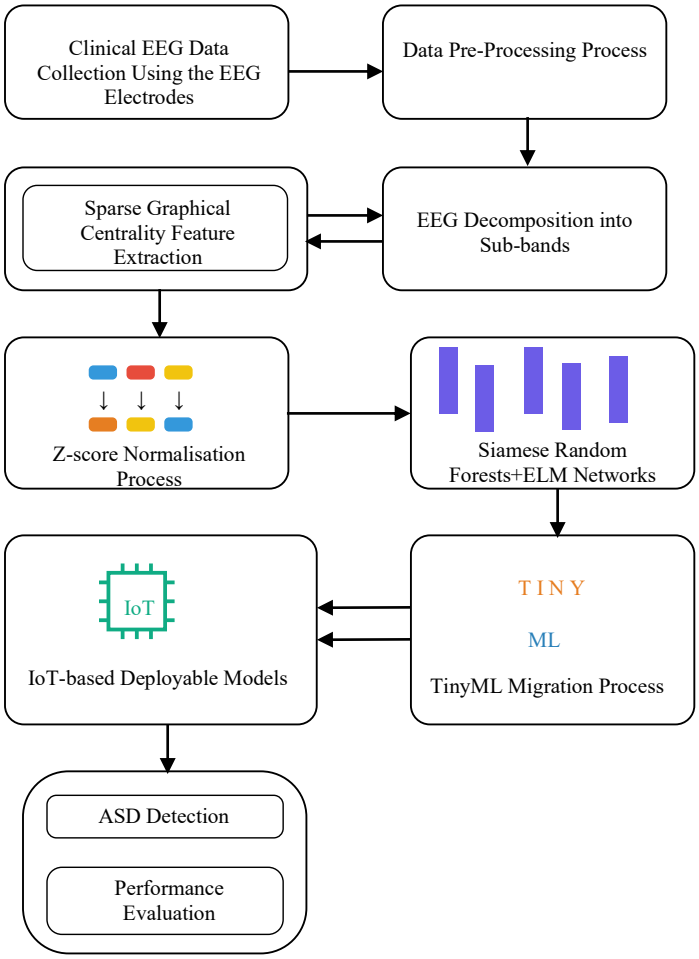


Fig. 1: Systematic Architecture for the Suggested Framework

The paper provides a systematic architecture of the proposed framework to detect ASD based on EEG signals in fig. 1. Architecture begins with EEG data acquisition and proceeds through the pre-processing phase using bandpass filters and artifact removal techniques. The Discrete Wavelet Transform (DWT) is used in extracting features by splitting the EEG data in order to obtain multiresolution features. Feature extraction is done through sparse graphical centrality in order to minimise computational burden. For classification, Siamese Random Forest, as well as the ELM algorithm, are considered.

EEG Data Collection Process

In this study, real-time EEG clinical data was gathered from 75 patients, which was then used to train and test the model. The data includes around 5,786 sessions collected from these 75 patients, recorded at a sampling rate of 250Hz using 21 scalp electrodes arranged according to the 10-20 system. The EEG recordings are done in a quiet room, with participants awake, sitting comfortably in a chair, and keeping their eyes open while staying relaxed. Fig. 2 shows the raw EEG data from individuals with autism and those without. Table 2 provides the statistical breakdown of the dataset used. The study involved 37 males and 38 females, with an average age of 11 years. The experiment followed the Declaration of Helsinki (Oh et al., 2021) and met the ethical standards for biomedical research. Each EEG recording was labelled by certified neurophysiologists, who identified the exact start and end points of various neurological events, including focal, generalised, and complex partial seizures associated with ASD patterns.

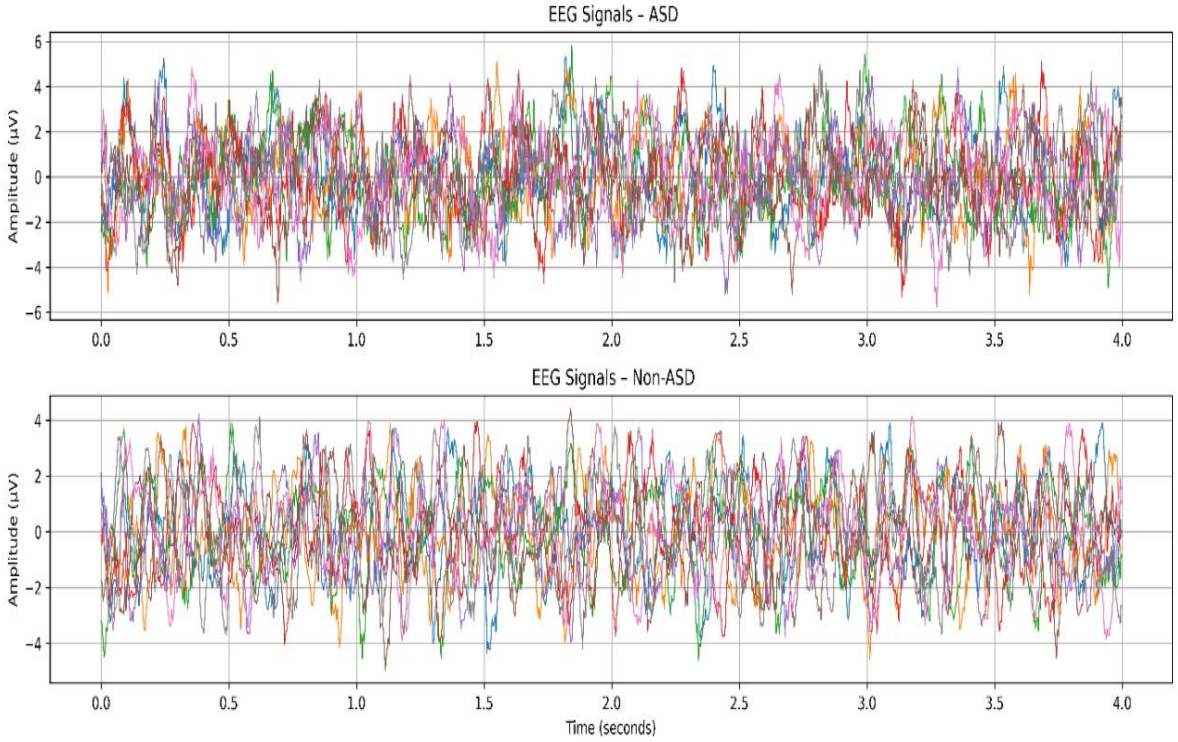


Fig. 2: Non-ASD and ASD Based EEG Signals Recorded from the Different Individuals

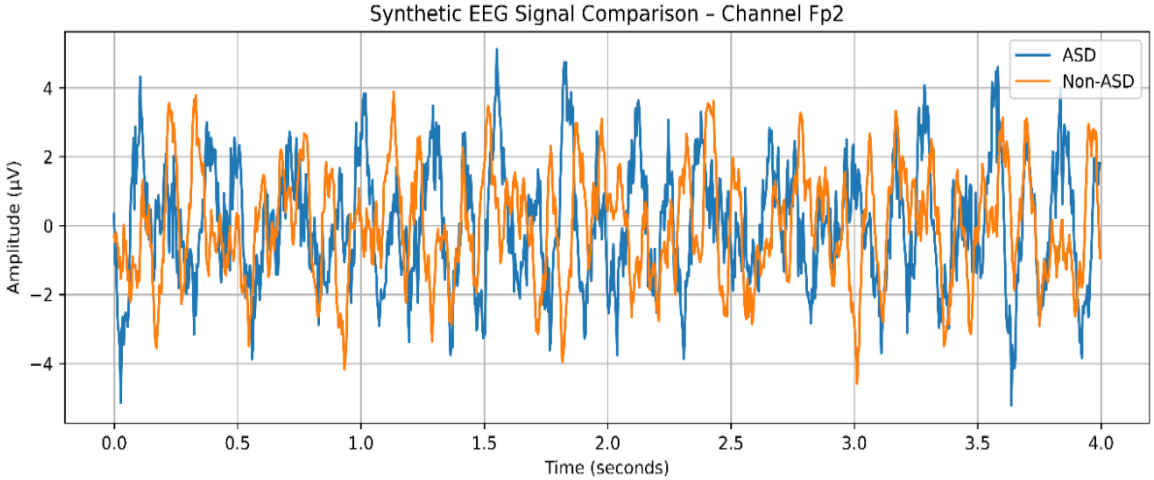


Fig. 3(a): EEG Signals Obtained from People Suffering From ASD

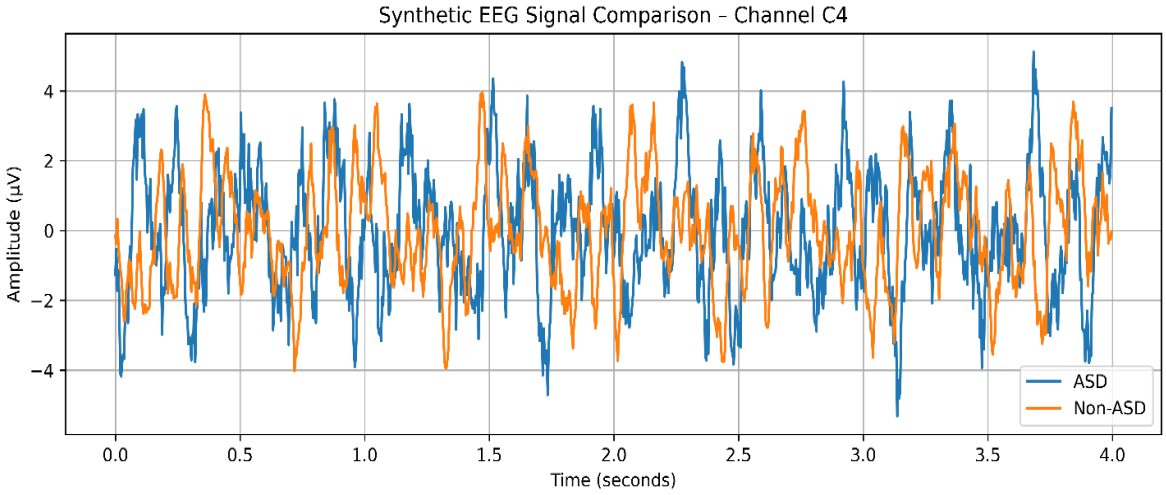


Fig. 3(b): EEG Signals Obtained from Normal Individuals

Fig. 3(a-b): Sample EEG Signals Created from the Different Lobes Using the EEG Electrode

In fig. 3 (a) represents the EEG signals obtained from people suffering from ASD. This is very helpful in the detection of ASD, considering that these are some of the characteristics of people who suffer from the disorder. Fig. 3 (b) represents the EEG signals obtained from normal individuals. The differences in the patterns between those of the people suffering from ASD are helpful in classifying the disorder. The raw EEG data signals are used to show the variation in brain activities of people with ASD and non-ASD individuals.

Table 1: Presents a Description of the Dataset Used in the Research

Sl.No	Description in the Datasets	Specifications of the Dataset
1	No of Session recordings	5,786
2	Sampling Frequency	250Hz
3	No of ASD Classes	02
4	Recording channels	21
5	Type of Files stored	EDF

Table 1 shows a description of some of the main characteristics of the data set that was used in this study. These characteristics include the total number of sessions, which is 5,786; a sampling rate of 250Hz; and the binary classification of ASD. There are 21 channels on which the EEG signal is recorded, and the data file format used for storing the EEG data is the EDF (European Data Format) format.

EEG Pre-processing

Various stages are incorporated in this study for processing of the EEG signals to increase the accuracy of the developed ASD model. This includes segmenting the EEG signal data from the clinical environment in 30-second intervals that guarantee uniformity in brainwave activity during each interval. A Butterworth fourth-order notch filter is then used to process the data, where particular configurations of the notch filter help in distinguishing between different types of brainwaves, like alpha, beta, gamma, theta, and delta. The filter is configured to maintain minimal ripple (0.0102) and provide strong suppression of unwanted frequencies (60 dB stop band attenuation). This technique filters the noises created by high-frequency muscle movements and low-frequency drifts. In the final stage, ICA (Independent Component Analysis) is applied to remove the artifact-related components, retaining the most cortical signals related to ASD-specific neural dynamics. Finally, discrete wavelet transforms (DWT-db4) are applied on each sub-band to provide the multi-scale multi-resolution datasets that provide more insight into temporal features to identify the short-term and non-stationary patterns in each EEG sub-band. The proposed hybrid technique with the filtering and DWT, which is deployed for the pre-processing process, is normalised using Z-score normalisation techniques, which are more useful for the feature extraction and interpretability analysis.

Sparse Centrality Feature Extraction Process

The existing feature extraction and model designs used for EEG-based ASD systems introduce major challenges, such as Computational inefficiency and non-interpretability problems, which make it unsuitable for deployment in IoT

devices. To overcome this challenge, this research introduces the Sparse Graphical Centrality Feature extraction process. In the first stage, decomposed sub-bands are used to extract the brain centrality maps using the Pearson Correlation Coefficient, which delivers the dense correlations from each sub-band. In order to reduce the complexity of computations, the Sparse Centrality method is proposed, that keeps the most important and strong links that distinguish both the ASD and Non-ASD systems. This proposed strategy is used to compute and subsequently identify the functionally important EEG that constitute the major role in classifying the ASD patterns. Table 2 presents the Sparse centrality features with its specification, which are extracted using the proposed technique.

Table 2: Sparse Centrality Measurements for the EEG Brain Functional Graphs

Sl.No	Centralities Extracted	Descriptions
01	Sparse Degree Centrality	Reflects the Number of significant functional connections that differentiate the ASD and Non-ASD patterns.
02	Sparse Centrality Drifts	Measures the abrupt changes in the brain activity that make the difference between ASD and Non-ASD
03	Sparse Eigen Vector Centrality	Used for computing the centralities of EEG nodes in the network
04	Sparse Stable Centrality	Captures the Stable and non-stable ASD patterns from the EEG nodes.

As the clinical dataset contains 21 electrodes, nearly 1005 dense (21 channels x4 centrality featuresx5bands) features are extracted. Since the research incorporates the sparse techniques, the total features are then reduced to 40 without disturbing any energy levels in the EEG features. After the feature reduction process, Z-score normalisation is applied to the features to normalise the data. These features are then fed to the TinyML for an efficient detection of ASD patterns.

Siamese Random Forest Networks

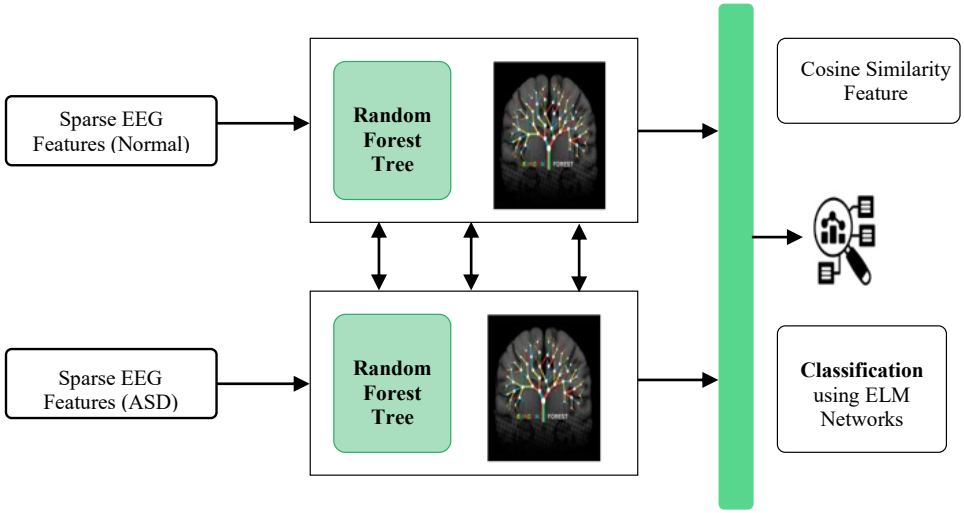


Fig. 4: Proposed Siamese Random Forest Networks for Classifying the EEG –ASD Patterns

To obtain high generalisation in the model, ensuring less computational efficiency, the suggested network incorporates the Siamese Random Forest networks with the functionalities shown in fig. 4. This novel integration provides robust non-linear decision boundaries, which can inherently incorporate an interpretability process. The proposed model consumes only a little computation overhead, suitable for resource-constrained devices. Siamese Learning Network is a paradigm in which the model learns to determine whether two EEG patterns belong to the ASD or Normal classes. Unlike the conventional classification, these models operate on a similar pair of inputs rather than class labels. For constructing the Siamese Model, a pair of Random Forest Models is added, in which the trees are shared to differentiate the normal and ASD patterns. Each Siamese pair consist of 'N' decision trees in which the mapping of each feature is done independently. Finally, the voting methods based on the Cosine Similarity function are applied using equation (1).

$$Y = \text{Cosine Similarity}\,(RF1, RF2) = \text{Cos}(\theta) = \frac{R1.R2}{||R1||.||R2||} \qquad (1)$$

$Equation(1)$ is used to compute the similarity scores with respect to reference EEG feature vectors using cosine similarity. The final classification is obtained through classification networks, where reference samples with higher similarity exert a stronger influence. This strategy provides scale-invariant decision-making, improved generalisation under limited data, and computational efficiency suitable for IoT-based ASD detection.

Extreme Learning Machines as Classification Layers

Extreme Learning Machines are a variety of feed-forward neural networks, which are characterised by low training error and show high functionality when implemented on new, unknown situations. The detailed way ELM works is explained in (She et al., 2018). Unlike regular feed-forward networks, the hidden layers in ELM do not require ongoing adjustments. Instead, the weights and bias values for the neurons are chosen randomly at the start and stay the same throughout the learning process. This design significantly reduces the computational complexity and training time, making the model specifically dedicated to real-time resource-constrained environments. The mathematical expression of a single-layered ELM's output function is given below.

$$G(x) = \sum_{i=1}^{N} U_i B_i(x) = B(x)U \quad (2)$$

Where x = input features from the encoder-decoder

U = output weight vector and $B(x)$ is the output hidden layer. Applying the minimal non -linear least square methods for analysing the output weight vectors

$$U' = B^{*}O = B^{T}(BB^{T})^{-1}O \quad (3)$$

Where B^{*} → is the inverse of H, known as the Moore−Penrose generalised inverse.

Hence, the output function can be found by using the above equation by combining equation (2) and (3)

$$f_L(x) = B(x)U = B(x)\, B^{T}(BB^{T})^{-1}O \quad (4)$$

Where $B(x)$ is the input feature maps, U is the temporal matrix, which is solved by the Moore−Penrose generalised inverse theorem, denoted by B^{T}, C is a constant, B and O are the weights and bias factors of the network. For an effective classification of ASD patterns, a binary loss function is incorporated, which is mathematically expressed in equation (4).

Tiny Model Deployment Process

The proposed framework works on IoT devices, and it's still quite difficult because of some natural limitations, like not much computing power, not a lot of memory, and not enough battery life. To address these limitations, this research proposes the lightweight Tiny ML-based Siamese Random Forests (SRF) on small IoT devices while maintaining energy efficiency. Fig. 5 illustrates tensorflowLite[] is employed as the primary native support for transforming the designed model into hardware centric Tiny ML model. To ensure efficient deployment on resource-constrained IoT embedded CPUs, hyperparameters are optimised to achieve the trade-off between the flash memory consumption and predictive performance. Quantisation is used to adjust the network's settings in a way that works well with the hardware. This helps make the system practical for real use while keeping the classification results reliable and accurate. Algorithm-1 presents the complete algorithm for the working mechanism of the suggested network (Table 3).

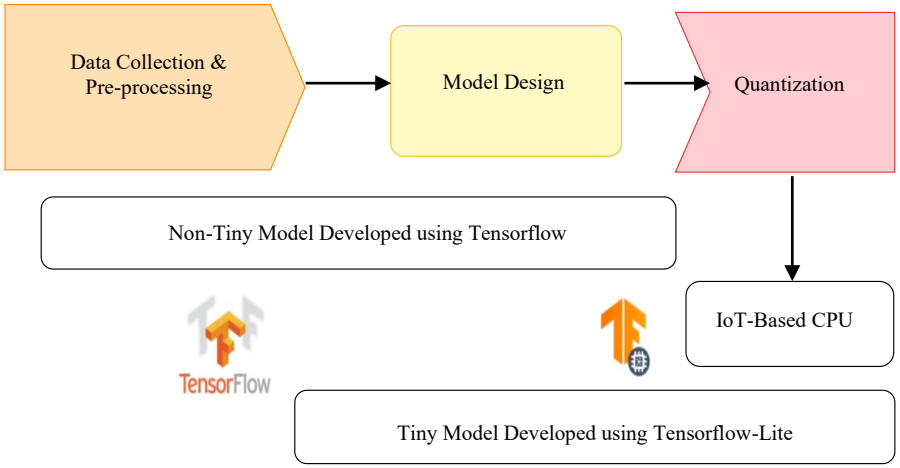


Fig. 5: Overall Workflow for the Conversion of the Proposed FSL to TinyML Model

Table 3: Algorithm-1// Working Mechanism of the Suggested Framework

Step	Algorithm-1// Working Mechanism of the Suggested Framework
	Start
1	EEG Clinical Dataset Collection Process
2	EEG pre-processing techniques
3	Feature Extraction Process
4	Similarity Features detected using the Siamese Networks
5	Classification of the ASD using ELM layers
6	Deployment on the Memories of IoT-based Devices
7	Performance Evaluation Process
	End

Algorithm-1 outlines the suggested framework that uses EEG signals to identify ASD in patients. First, real-time EEG data from patients is gathered, with each session showing either typical brain activity or a pattern associated with ASD. The collected data is then processed and cleaned to remove any noise or unwanted interference. Important features are extracted from the EEG data using wavelet transform and graphical sparse centrality methods. These features are analysed using a Siamese network, which helps in recognising similar patterns within the data. Following this, a classification process is carried out using ELM layers, which allows for fast and efficient detection. The model is then adapted to run on IoT-based devices, making sure it works well even on hardware with limited resources. Finally, the effectiveness of the algorithm is checked using several evaluations.

Experimental Validation

The entire experimental code is coded on a PC workstation with an Intel I7 processor having a 3.0 GHz clock rate, 32 GB of RAM and a 1TB hard disk. It used Python 3.12-based machine learning algorithms. The designed model runs on both the CPU and an embedded IoT board. Its performance was checked using measures like accuracy, precision, and F1-score. Additionally, energy usage, memory use, and latency, which is the time taken for a process, are also measured and compared with other existing models. To assess the suggested framework, performance metrics are used.

Mathematical Expression for the Evaluation of the Suggested Framework

The measures of evaluation applied in the paper to evaluate the proposed ASD detection framework are:

Accuracy: This measure is used to quantify the total accuracy of the model (Equation 5)

$$\frac{TP+TN}{TP+TN+FP+FN} \quad (5)$$

Here in equation (1), TP is True Positive Values, TN is True Negative Values, FP is False Positive, and FN is False Negative Values.

Sensitivity or recall in equation (6) is used to determine the capability of the model to identify all positive instances correctly.

$$\frac{\text{TP}}{\text{TP+FN}} \quad (6)$$

Precision: It is a measure of the percentage of correct positive predictions of the model out of all positive predictions of the model ($Equation\ 7$)

$$\frac{TN}{TP+FP} \quad (7)$$

F1-Score in equation (8) is defined as the harmonic mean of precision and recall is the F1-score, which gives a balanced indication of how the model is performing in both the detection of positive and reduced false positives.

$$2 \times \frac{Precison*Recall}{Precision+Recall} \quad (8)$$

Each metric has its own role and helps check different parts of how well the model predicts ASD. These metrics are used to see how good the model is at finding autism patterns in EEG data. It shows how well the model can spot autism early on. With these evaluation tools, the model's balance between precision and accuracy, and how well it avoids making wrong classifications, is determined.

Performance Outcomes

In order to analyse the process of the machine learning approach, the confusion matrix and ROC-AUC properties are applied as efficient methods. Fig. 6(a) and fig. 6(b) is the confusion matrix of the presented model to detect the patterns of ASD and Non-ASD, which clearly indicates that the model produces high TP results with reduced false alarm values in both CPU and Embedded CPU.

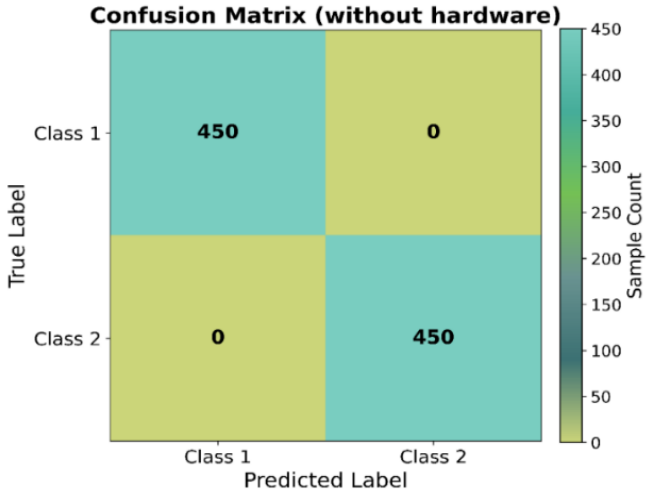


Fig. 6(a): Confusion Matrix of the Suggested Model In CPU

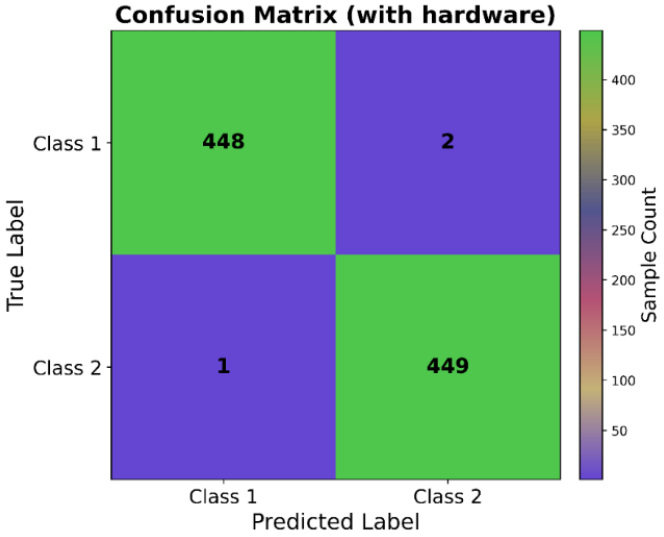


Fig. 6(b): Confusion Matrix of the Suggested Model Embedded IoT in CPU

Fig. 7(a) and 7(b) shows the receiver operating characteristics (ROC) of the proposed model in identifying ASD and Non-ASD patterns. The ROC curve indicates that the model has an AUC of 1.00, meaning it can accurately distinguish between ASD and Non-ASD brain patterns at various thresholds. The model performs similarly well when run on embedded CPUs. Fig. 7 also shows that the model maintains high sensitivity while keeping false alarm rates low, making it a good choice for early ASD screening and predictive monitoring systems.

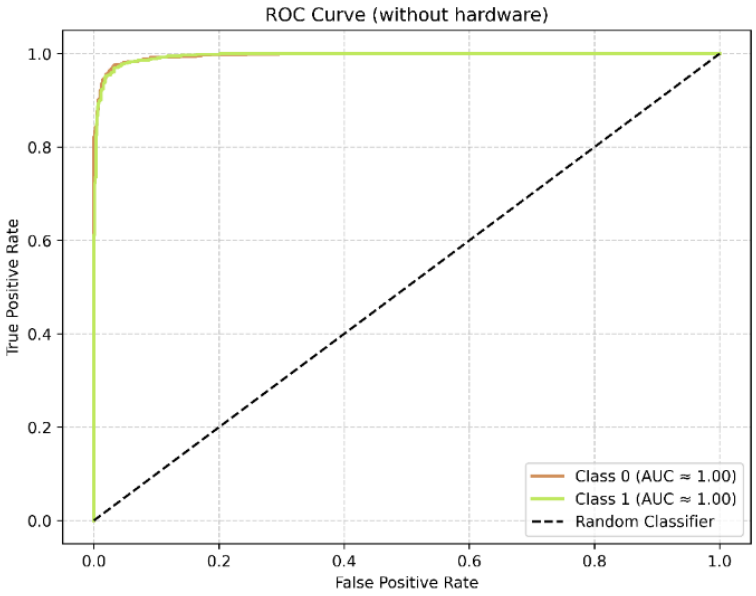


Fig. 7(a): ROC-AUC of the Suggested Model in Traditional

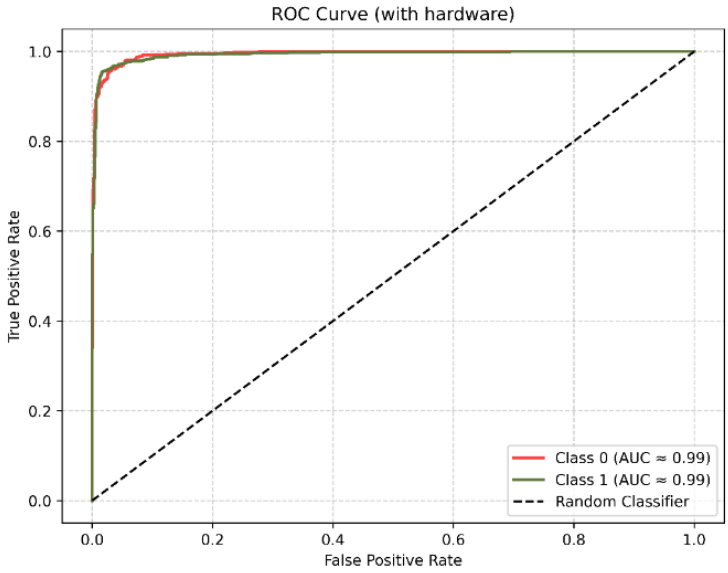


Fig. 7 (b): ROC-AUC of the Suggested Model in Embedded CPU

The results were compared with other common machine learning methods to show that the proposed model works. Fig. 8 and 9 clearly show that the suggested model performed the best, with an accuracy of 0.99, a precision of 0.984, a recall of 0.983, and an F1-score of 0.99. The Support Vector Machines (SVM) and K-Nearest Neighbors (KNN) models had average performance in detecting both ASD and Non-ASD patterns. The experiments show that the proposed model is better at identifying ASD and Non-ASD brain activities than other models. It is clear that combining Siamese Random Forest with Extreme Learning Machines gives the best results in detecting ASD and Non-ASD patterns, especially when it comes to CPU efficiency.

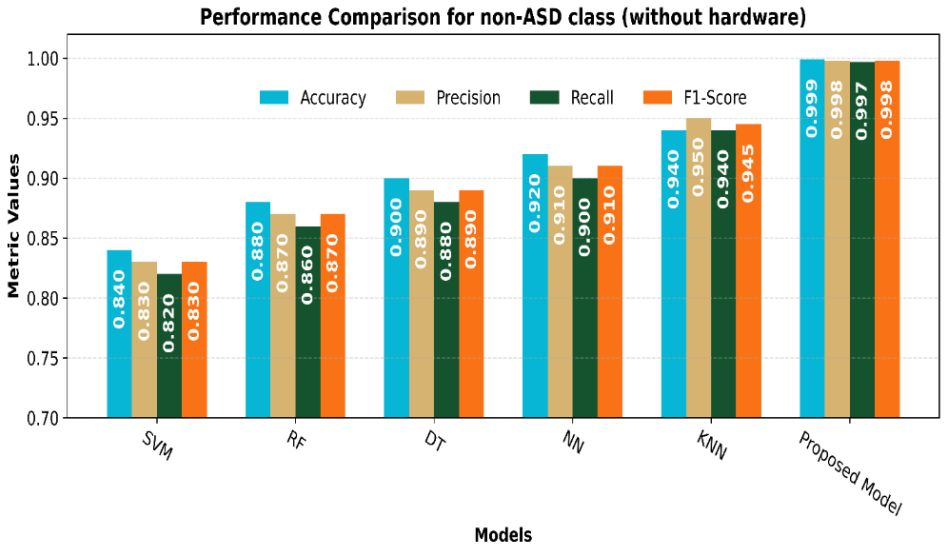


Fig. 8: Performance of the Different Models in Detecting the Non-ASD Patterns

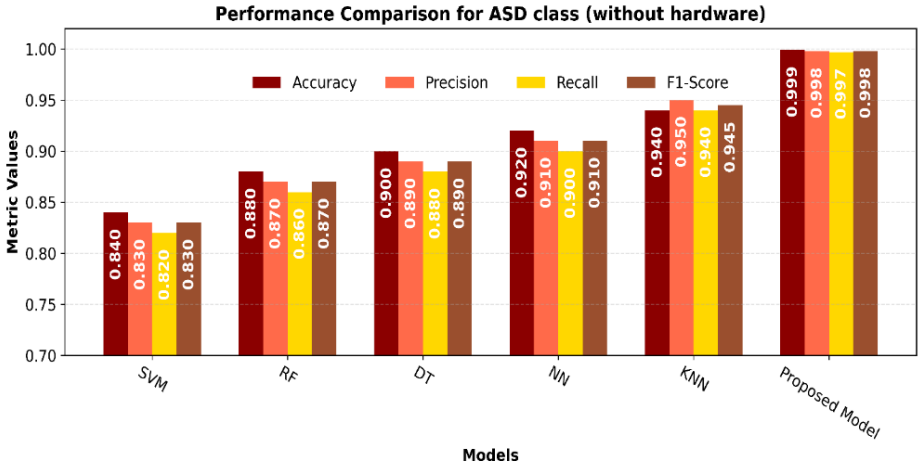


Fig. 9: Performance of the Different Models in Detecting the ASD Patterns

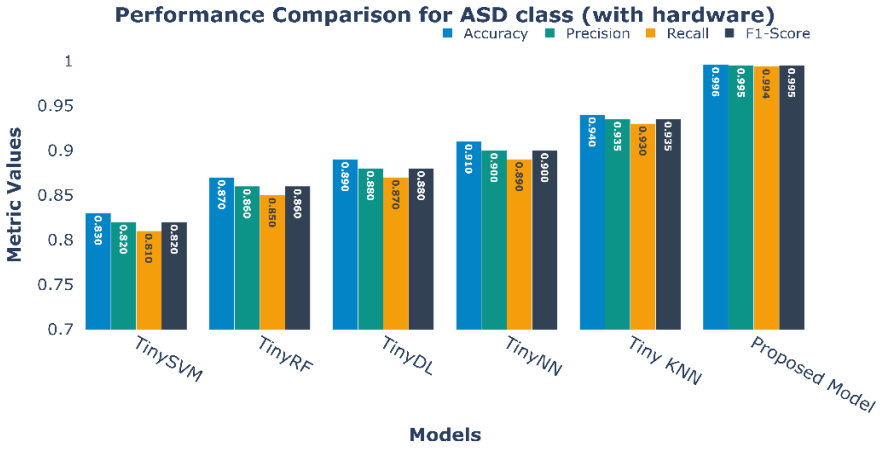


Fig. 10: Performance of the Model in Detecting the ASD Patterns in Embedded CPUs

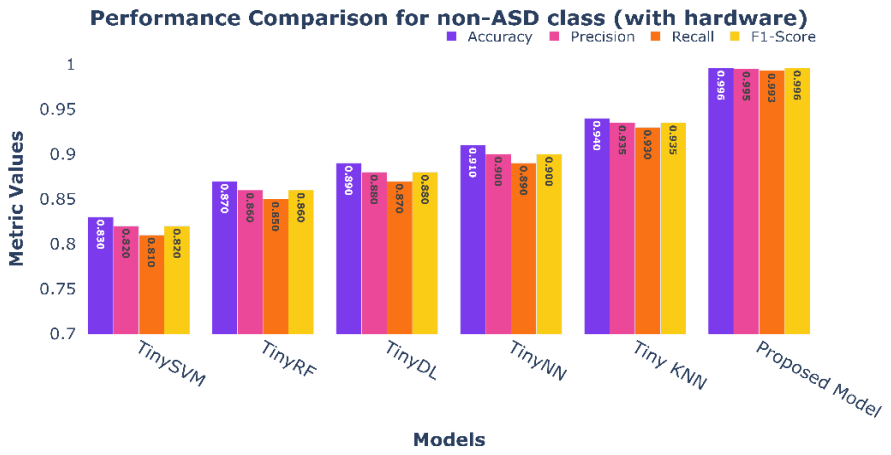


Fig. 11: Performance of the Model in Detecting the Non-ASD Patterns in Embedded CPUs

Fig. 10 and fig. 11 show how well the model can detect ASD and Non-ASD patterns when deployed on Embedded CPUs. All the baseline models are turned into tiny models using the process described in section 3.7. Fig. 11 and fig. 12 show the model's performance in detecting ASD and Non-ASD patterns on embedded CPUs. Fig. 11 presents the proposed Siamese model, which performs the best in detecting ASD patterns. The performance of the other models in detecting non-ASD classes is shown in fig. 12. The graphs depict that the proposed model performs better than the others in detecting both ASD and non-ASD classes.

Computational Analysis

Table 4 shows how well different models perform on a CPU. The proposed Siamese model uses less memory, has lower latency, and requires fewer FLOPs compared to other models, especially when compared to the traditional RF. Although the RF performs slightly better than the existing models, the detection performance of the suggested framework is much better than that of the conventional RF networks. This experiment shows that the proposed model is significantly better in terms of performance when run on a CPU compared to the other models.

Table 4: Computational Performance of the Suggested Framework in CPU

Algorithm	**Computational Performance (CPU)**				
	Inference Time (Secs)	Memory (MB)	FLOPS (Secs)	Computational Time (secs)	No. of Design Parameters
SVM	18.22	177	102	49.99	Kernel =RBF with high C and beta values
RF	12.99	120	90	20.88	No. of Estimators =100, No of depth=10
KNN	18.5	190	120	40.83	K=5
DT	16.88	180	101	21.99	Maximum depth=10
Suggested Model	12.44	**115**	**90**	**19.99**	No of estimators=77, No. of depth=10

Table 4 shows how well the different models perform on the Embedded CPU. The proposed model uses less memory, has lower latency, and requires fewer FLOPs compared to the other models, yet it performs better than the other tiny learning models. Although Random Forest and Decision Tree have a slight advantage over some existing models, the detection performance of the suggested framework is much better than the others. These experiments prove that the proposed model is significantly better than the other models when running on the Raspberry Pi, as shown in table 5.

Table 5: Computational Performance of the Suggested Framework in Raspberry Pi Model 3B+

Algorithm	**Computational Performance (Raspberry Pi)**				
	Inference Time (Secs)	Memory (MB)	FLOPS (Secs)	Computational Time (secs)	No of Design Parameters
Tiny SVM	18.22	177	102	49.99	Kernel =RBF with high C and beta values
Tiny RF	12.99	120	90	20.88	No of Estimators =80, No of depth=08
Tiny KNN	18.5	190	120	40.83	K=5
Tiny DT	16.88	180	101	21.99	Maximum depth=08
Suggested Model	12.44	**115**	**90**	**19.99**	No of estimators=61, No. of depth=08

Comparison of Accuracy with Existing Models

Table 6: Comparison of Performance Metrics of the Proposed Model and Existing Models for ASD Detection

Paper	Methodology	Accuracy
Proposed Model	Sparse TinyML + Siamese RF + ELM	0.99
(Alarfaj et al., 2025)	LSTM + SMOTE	0.89
(Singh & Kakkar, 2024)	Maxout + fuzzy hybrid	0.93
(Alhassan et al., 2023)	Embedded ML + entropy	0.96

Table 6 gives a comparison between the performance of the proposed model and some models found in the literature. The proposed model, incorporating Sparse TinyML, Siamese RF, and ELM, is capable of exhibiting remarkable performance when it comes to diagnosing ASD from EEG signals, scoring an accuracy of 0.99. The other models (Alarfaj et al., 2025; Singh & Kakkar, 2024), among others, use varied methodologies in detecting seizures (deep learning algorithms) and use fuzzy hybrid approaches, respectively. Although accurate in its own right, its maximum accuracy also lies between 0.89 and 0.96.

Ablation Study Outcomes

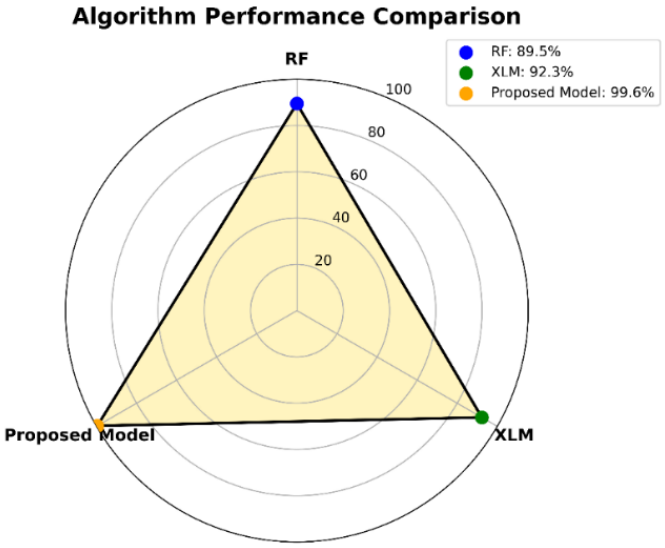


Fig. 12: Ablation Outcomes for the Different Components in the Suggested Framework

Fig. 12 evidences that all the components in the suggested framework have played a significant role in distinguishing the ASD and Non-ASD patterns. Fig. 12 clearly shows that the performance of the suggested model has been enhanced by the synergetic contribution of all components, which includes the data pre-processing techniques. The result outcomes demonstrates that the ASD patterns are more effectively characterized by the integration of all models.

Conclusion and Future Enhancement

The proposed methodology introduces an IoT-enabled Siamese Network which is effective for classification of ASD and Non-ASD patterns using EEG signals. The proposed framework includes the following components: 1) EEG data generation and collection, 2) EEG pre-processing, 3) Siamese network design, 4) TinyML model, and 5) performance evaluation. The framework begins with the collection of EEG clinical data, followed by pre-processing and the application of a hybrid Siamese model. The model is then quantized and deployed on an IoT-based embedded CPU. Extensive experiments are conducted using metrics such as accuracy, precision, recall, specificity, F1-score, FLOPS, memory usage, and inference time. To validate the model's superiority, state-of-the-art learning models are also tested during the experiments. Additionally, the model was validated on various hardware platforms, including a CPU, smart edge phone, and Raspberry Pi Model 3B+. This proposed model results shows that it excels in detecting ASD and Non-ASD patterns from EEG signals, achieving an accuracy of 0.99, precision of 0.984, recall of 0.98, and an F1-score of 0.99 across multiple hardware platforms. Although the model demonstrates high performance with low computational requirements, it still needs to be validated with larger clinical datasets and scaled for deployment across a variety of IoT devices.

Further validation of this study using larger clinical datasets may prove useful in order to ensure that the model used here is generalizable across a wide variety of demographics and diseases. Extending the usage of the model to clinical monitoring systems can further increase its utility in providing consistent monitoring of ASD over time. Further optimization of the model to run on other low-powered IoT devices including smartphones and edge devices can make sure that the model is efficient and effective on all sorts of devices. In addition, longitudinal studies may be conducted to see whether the model can monitor ASD patterns over time, providing some useful information regarding early interventions.

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