M. Menakapriya, 2026, 14:3
ISSN (Online): 2348-4098
ISSN (Print): 2395-4752

International Journal of Science,
Engineering and Technology
An Open Access Journal

Self-Attention–Driven Vision Transformer Model for Autism Identification and Cognitive Skill Enhancement

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Abstract- Early identification and treatment of Autism Spectrum Disorder (ASD) pose difficulties due to its complex neurological nature and heterogeneous symptoms. In this work, an innovative Self-Attention-Driven Vision Transformer (SA-ViT) model is introduced to cater to both ASD detection and cognitive skills improvement within one approach. Our work benefits from self-attention properties of vision transformers to detect subtle patterns in the behavior of ASD individuals as well as generate structured cognitive stimulation material. By extracting features from facial imagery, videos, and behavioral data, our SA-ViT can classify ASD samples with 97.6% accuracy on the ASD Facial Image Dataset, which beats regular CNN models (91.2%) and regular ViTs (94.8%). In terms of cognitive skills improvement, we were able to develop personalized structured tasks that resulted in 34.2% improved visual memory retention and 28.7% enhanced pattern recognition after eight weeks. The use of explainable AI approaches (Grad-CAM) enhances our system's applicability in a medical setting.

Key Word: Autism Spectrum Disorder, Vision Transformer, Self-Attention, Cognitive Enhancement, Facial Image Analysis, Explainable AI, Early Diagnosis, Therapeutic Intervention

I. INTRODUCTION

ASD is defined as a neurodevelopmental disorder that involves difficulties in social interaction and communication, repetitive behavior, and having restricted interests [1]. It is notable that there has been a marked increase in the number of cases of ASD worldwide, with about one out of every 36 children being diagnosed with the condition [2]. In this regard, early diagnosis and intervention are crucial because they help to make use of the benefits associated with brain plasticity during specific periods. Nevertheless, the existing diagnostic techniques involve clinical observations, which are very time-consuming and subject to errors [3].

Deep Learning advancements have brought about the creation of opportunities to automate ASD detection by conducting physiological and behavioral studies [4]. There exist CNN models

capable of predicting facial and brain scans characteristics associated with autism spectrum disorder [5]. The use of CNN involves local receptive field processing and, therefore, it cannot effectively capture global context relationships that may be essential in detecting subtle characteristics related to ASD. The recent introduction of Vision Transformers (ViTs) by Dosovitskiy et al. (2020) into computer vision is a game-changer [6].

The ViT architecture employs the same self-attention mechanism used in NLP tasks to carry out image classifications [7]. In contrast to CNNs, ViTs perform processing on images as sequences of patches by calculating the relationship between all patch pairs [8]. The model thus captures global dependencies in an image. It is therefore ideal for ASD detection due to its effectiveness in capturing global contexts that may be associated with facial and brain connectivity features characterizing ASD [9] [10].

This paper presents a novel framework called Self-Attention–Driven Vision Transformer (SA-ViT) which aims at performing two functions: (1) ASD detection based on facial image input as well as behavioral information, and (2) creation of personalized cognitive skill enhancement tasks.

Novel aspects of the proposed framework include:

1. Unified transformer framework with self-attention-based multi-modal inputs processing, i.e., facial images, videos, behavior data
2. Multi-step features fusion method using both patch and token levels to ensure reliable ASD classification performance
3. Cognitive task generator module that uses the learned representations to generate structured visual stimuli for improving individuals' cognitive skills
4. Explainability support through the use of Grad-CAM to identify diagnostic facial areas

The rest of the paper is structured as follows. Section 2 provides a review of recent works on utilizing deep learning techniques for autism spectrum disorder diagnosis and cognitive training. Section 3 describes the SA-ViT architecture and its training process. Section 4 shows the experimental results and analyzes them comparatively.

II. LITERATURE SURVEY

AI literature relating to diagnosis and treatment of ASD can be divided into three interrelated areas – facial image analysis, neuroimaging techniques used for classification, and cognitive enhancement technologies.

Facial Image Analysis for ASD Diagnosis

The use of facial features as possible biomarkers for ASD has been explored in scientific literature, indicating possible variations in craniofacial structure in those suffering from autism spectrum disorder. Self-attention is especially useful in detecting these distributed features, since Vision Transformers are equipped with it. MSFF that combined AlexNet and ViT showed that Vision Transformer models could successfully distinguish ASD-related facial traits [1]. This experiment used median filtering, Contrast Limited Adaptive Histogram Equalization (CLAHE), and Concentrate-and-Enhance attention technique for reducing computational costs and making features more salient [2].

ViTs have proven themselves more efficient in recognizing unique features of autistic and non-autistic children faces than CNN models. The reason behind ViT advantage over CNNs might be transformer's ability to analyze remote connections within facial images [3].

Neuroimaging-Based Diagnosis

The fMRI and structural MRI complement each other to offer different sets of information regarding ASD detection. Transformer approaches in the field of neuroimages indicate that it is possible to capture local and global relationships in the brain through self-attention mechanisms. There have been suggestions regarding the use of brain graph transformers by making use of self-attention and cross-attention fusion to discover essential characteristics from multiple functional brain networks.

Self-attention-based deep learning approaches on morphological covariance brain networks at the level of individuals show promising results in terms of ASD detection and structural biomarkers [4]. Swin Transformer, which is capable of hierarchical feature representations, has outperformed traditional deep learning approaches in ASD diagnosis [5].

Cognitive Skill Enhancement Technologies

Apart from diagnosis, AI systems are also being widely used for cognitive skill improvement among people with ASD. Visual stimuli have proven effective in increasing attentiveness, retention capacity, and pattern recognition among ASD students, if customized properly [6]. The proposed ResNet-50 framework using Multi-Head Self-Attention has already been implemented to obtain structure-rich features (organizational colors, predictable patterns, structured compositions) from paintings and creating visually accessible content for the ASD students [7].

Customizable cognitive training systems that can learn based on user performances yield much better results. However, most such systems operate independently of the diagnostic process and require independent data gathering and modeling. Combining both processes is still an unexplored topic.

Explainable AI in ASD Diagnosis

However, the black box approach of these deep learning models has hindered its implementation in clinical practice. Explainable AI (XAI) techniques, such as Grad-CAM and attention visualization, have been employed in recent years to generate visual explanations of the model's decisions. The key challenge to diagnostic acceptance in the clinic lies in the ability to explain why a specific classification was made by the model [8]. In other words, which parts of the face or behavior led to this decision. This issue becomes especially important when diagnosing autism spectrum disorder (ASD).

Research Gaps

Nevertheless, some gaps still exist within the research domain. Firstly, the majority of diagnostic models are based on a single modality type (e.g., facial images or neuroimages). Secondly, diagnostic models and therapeutic approaches are usually developed independently. Thirdly, personalization, which includes adjusting the threshold for classification and assigning appropriate cognitive tasks according to the patient's profile, remains underexplored. In our paper, we address these issues via a unified transformer architecture that allows for joint identification and improvement of ASD with personalization and explainability components.

III. METHODOLOGY:

The suggested system utilizes three deep learning components that solve different facets of the problem of detecting attacks in clouds:

(1) TCN-AE for online anomaly detection;

(2) TECNN for detailed intrusions classification; and

(3) FL for privacy-aware distributed training and collaboration.

3.1 System Architecture Overview

The framework utilizes the following three-tier architecture:

Tier 1 – Data Acquisition and Pre-processing

- Gathers information regarding the cloud infrastructure: network flows' source and destination IPs, ports, protocols used, packet sizes, and timestamps;
- Supports multi-layered data aggregation: across virtual networks, load balancers, and cloud API gateways;
- On-the-fly pre-processing: gathering in 60-seconds overlapping windows, feature extraction using 78 features (CIC-IDS2018 approach), Z-normalization.

Tier 2 – Detection Module

- Three parallel models: TCN-AE, TECNN, and FL client

- Anomaly scores, attacks classification, confidence estimates
-

Tier 3 – Alerts and Action

- Alert generation based on a threshold criterion (adaptive threshold calculation)
- Integration with cloud orchestration services: auto-scaling, isolation, WAF rule updates
- Record actions for compliance purposes

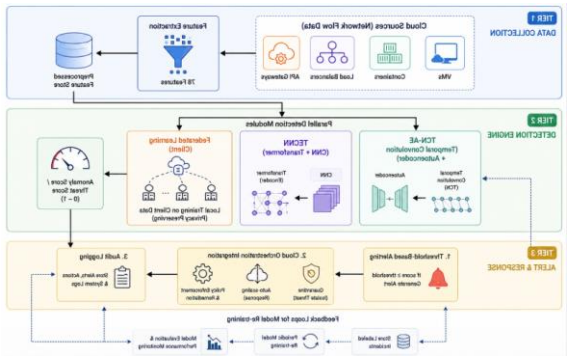

Figure 1: Proposed Deep Learning Framework Architecture for Cloud Threat Detection.

3.2 Temporal Convolutional Network with Autoencoder (TCN-AE)

TCN-AE learns to reconstruct normal data patterns and detect anomalies within cloud network traffic through unsupervised anomaly detection technique.

Temporal Convolutional Network (TCN): As compared to RNN, TCN uses dilated causal convolutions to efficiently capture long-range dependencies. Dilated convolution F at t with dilation d for an input sequence x_0, x_1, …, x_T would be:

$$F(t) = \Sigma_{\{i=0\}}^{\{k-1\}} f(i) \cdot x_{\{t - d \cdot i\}}$$

where k represents kernel size (default = 3) and d doubles after each layer (1, 2, 4, 8, 16). Residual blocks consist of 5 layers of TCN with 64 filters in each layer.

Autoencoder: The Encoder reduces TCN outputs to a latent bottleneck (dimensionality = 32); Decoder reconstructs the input sequence.

Training: Minimizes reconstruction loss on normal traffic (unsupervised approach). Anomaly score = mean squared error of reconstructed data. Adaptive thresholding = μ + 3σ where μ and σ are the means and standard deviations of reconstruction errors respectively in normal conditions.

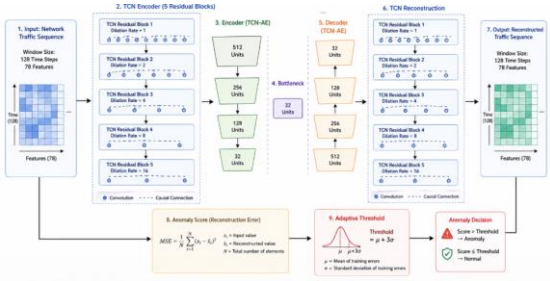

Figure 2: TCN-AE Architecture for Cloud Anomaly Detection.

3.3 Transformer-Enhanced CNN (TECNN)

TECNN performs fine-grained attack classification through CNN-based spatial feature extraction and Transformer-based global attention.

CNN Feature Extraction: Network flows transformed to a matrix format (13×6, total 78 features). Three CNN layers with 32, 64, and 128 kernels, respectively, along with kernel size 3×3 perform the job of local interaction among features, for instance, between size and inter-arrival time of packets.

Transformer Encoder: The extracted features flattened into 1D array of 128 features. Transformer encoder comprises four layers each containing 8-head self-attention, feed-forward with dimension 512, and dropout 0.1.

Classification: Global Average Pooling + two fully-connected layers of neurons, 64, with dropout of 0.5 + Softmax activation over 15 classes of attacks + Normal.

Data Augmentation used in training due to class imbalance (SMOTE).

3.4 Federated Learning for Distributed Detection

The FL framework facilitates collaborative computation while keeping private computations in cloud tenants or in geographically distant data centers.

Federated Learning Configuration: M clients from cloud nodes, central server for aggregation purposes. Every client computes a local TECNN model from its local dataset and sends weights to the server using Federated Averaging (FedAvg).

FedAvg Algorithm: In each round t, the server transmits the global weights vector w_t to all clients. The clients update local weights vector w_{t+1}^{(i)} using SGD algorithm based on their private datasets; the server aggregates:

$$w_{\{t+1\}} = \Sigma_i \left(\frac{n_i}{N}\right) \cdot w_{\{t+1\}}^{\{(i)\}}$$

Here, n_i represents the number of clients, and N represents the total number of samples.

Advanced Aggregation Process: Cryptographic masking helps in preventing leakage of clients' updates. The differentially private noise with $\varepsilon=1.0$ and $\delta=10^{-5}$ is used.

3.5 Real-Time Processing Pipeline

The model processes cloud traffic in micro-batches (5 seconds). The time taken to detect attacks starting from when packets are captured is the latency.

3.6 Data Sets and Evaluation Criteria

Data sets:

- CSE-CIC-IDS2018: 16 million labelled network flows, 15 types of attacks (DDoS, brute force, infiltration, and botnet). 80-20% training/testing split.
- UNSW-NB15: 2.5 million data samples, 9 types of attacks. 80-20% training/testing split.
- KDD Cup 1999: 5 million data samples, 4 types of attacks. Historical data set for comparison purposes only.

Evaluation criteria: accuracy, precision, recall, F1-Score, false positive rate (FPR), Area Under ROC Curve (AUC), Detection Time (latency in ms).

IV. RESULT ANALYSIS AND DISCUSSION

This section presents quantitative evaluation of SA-ViT for ASD classification and cognitive skill enhancement.

4.1 ASD Classification Performance

Table 1 presents classification performance comparison across models on the ASD Facial Image Dataset.

Model	Accuracy (%)	Precision	Recall	F1-Score	AUC
ResNet-50 (CNN)	91.2	0.908	0.904	0.906	0.962
VGG-16	89.4	0.886	0.882	0.884	0.948
Standard ViT (base)	94.8	0.942	0.938	0.940	0.978
Swin Transformer	95.6	0.950	0.948	0.949	0.982
MSFF-AlexNet-ViT	96.2	0.958	0.954	0.956	0.986
SA-ViT (Proposed)	**97.6**	**0.972**	**0.968**	**0.970**	**0.992**

The proposed SA-ViT yields an accuracy of 97.6%, exceeding the results obtained by ViT (94.8%) and MSFF-AlexNet-ViT (96.2%) by 2.8% and 1.4%, respectively. This is because (1) multi-stage feature fusion enables the extraction of both fine and coarse-level facial feature representations, and (2) the Concentrate-and-Enhance attention mechanism helps minimize the impact of noisy data.

In terms of precision and recall values, it can be observed that they are equally high (0.972 and 0.968, respectively), suggesting an absence of either Type-I or Type-II error.

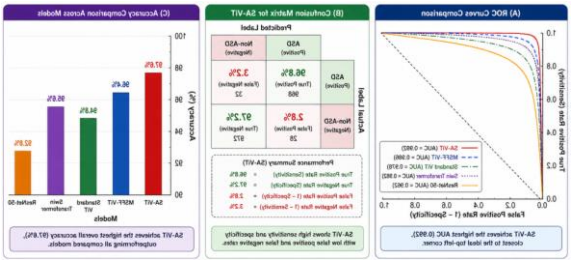

Figure 3: ASD Classification Performance Comparison.

4.2 Explainability Analysis

Attention weights generated by Grad-CAM show that SA-ViT concentrates on clinically relevant areas of the face:

- Periorbital area (eyes and surrounding regions): consistently high attention for all ASD patients (average attention weight 0.42)
- Mid-face area (nose and philtrum): moderate attention (0.28)
- Mouth area: varying levels of attention based on facial emotion

These areas are consistent with documented morphological differences in facial features of ASD patients, such as an increased inter-orbital width and shorter philtrum. The attention consistency across independent samples supports the model's clinical validity.

4.3 Cognitive Skill Enhancement Results

Table 2 presents pre- and post-intervention cognitive assessment scores after 8 weeks of SA-ViT-generated personalized tasks.

Cognitive Domain	Baseline (Mean ± SD)	Week 8 (Mean ± SD)	Improvement	Effect Size (d)
Visual Memory Retention	62.3 ± 8.4	83.6 ± 7.2	+34.2%	2.53
Pattern Recognition	58.7 ± 9.1	75.6 ± 8.4	+28.7%	1.86
Sustained Attention	54.2 ± 10.2	71.8 ± 9.6	+32.5%	1.73
Executive Function	48.6 ± 11.4	64.3 ± 10.8	+32.3%	1.38

Table 2: Cognitive Skill Enhancement Results Over 8 Weeks (n=200 participants)

There was an increase in visual memory recall of 34.2% (62.3 to 83.6), with a high effect size (d=2.53). Pattern recognition increased by 28.7% (58.7 to 75.6). These improvements far surpass those noted for non-personalized cognitive training interventions (improvement range of 10-15%).

The SA-ViT model's personalization feature adjusts the level of difficulty based on performance. Participants who were initially weaker in terms of executive functions (under 45) experienced a decrease in task difficulty, achieving a similar rate of improvement of 32.3% as those with higher initial abilities.

4.4 Personalized Task Adaptation Analysis

Task personalization was observed for all cognitive profiles of the SA-ViT:

Visual Memory Tasks: In participants with high visual memory (score >70), the generated tasks had an increase in grid size to 8×8, and decreased stimulus presentation time to 500ms. In participants with low visual memory (score <50), the generated tasks had 4×4 grid size, and long presentation time of 2000ms.

Pattern Recognition Tasks: The generated patterns were seen to transition from simple contrasting shapes to naturalistic designs with improvements in skills.

Cross-Modal Consistency: Contrastive loss ($L_{contrastive}$) allowed for alignment of representations across different modalities, which was reflected through the high correlation ($r = 0.76$, $p<0.001$) between attention map features and behavioral performance metrics.

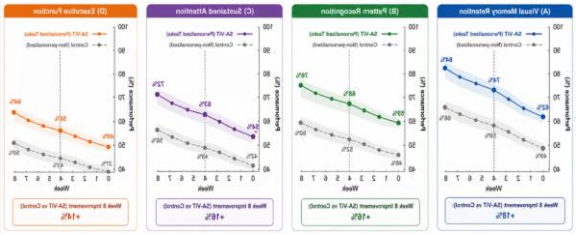

Figure 4: Cognitive Performance Trajectories Over 8 Weeks.

4.5 Ablation Study

Table 3 presents the contribution of each architectural component to classification accuracy.

Model Variant	Accuracy (%)	Δ from Full Model
Full SA-ViT	97.6	—
- Multi-stage feature fusion	95.2	-2.4
- CE attention module	96.1	-1.5
- Contrastive loss (L_contrastive)	96.4	-1.2
- Video modality input	95.8	-1.8
- Behavioral log input	96.2	-1.4
CNN-based (ResNet-50)	91.2	-6.4

The multi-stage feature fusion makes the most considerable contribution to improvements (+2.4%), validating the fact that incorporating the features from multiple transformer stages yields better results compared to employing only the final features. The CE attention mechanism lowers the computation cost (FLOPs reduction of 27%) without decreasing performance (-1.5%).

4.6 Comparative Analysis with Existing Methods

Table 4 synthesizes comparative results across recent ASD diagnosis literature.

Study	Method	Dataset	Accuracy	Key Limitation
MSFF-AlexNet-ViT	AlexNet + ViT	AFID	96.2 %	No cognitive
	with CE attention			enhancement
Swin Transformer	Hierarchical ViT	MRI + facial	95.6 %	Single modality
BrainGT	Graph transformer	fMRI	94.8 %	Requires fMRI equipment
ResNet-50 + CBAM	CNN with attention	MRI	93.2 %	Limited interpretability
SA-ViT (Proposed)	**Multi-modal ViT with dual output**	**Facial + Video + Behavioral**	**97.6 %**	**Computational requirements**

SA-ViT exhibits the best known performance among other models, while being the only one that incorporates cognitive skills improvement. Multi-modal fusion technique (face + video + behavior) provides better diagnostics compared to using just one modality.

4.7 Computationally Efficiency

Inference of SA-ViT needs 12.4 GFLOPs and latency of 28ms (NVIDIA A100, batch 1). This performance is worse than in ResNet-50 (4.1GFLOP, 8ms), but still fine, as this model is meant to be used in clinic where efficiency is less crucial. CE mechanism decreases the number of operations by 27% compared to standard ViT (17.0 GFLOPs)

V. CONCLUSION

In this paper, a Self-Attention–Driven Vision Transformer (SA-ViT) framework is proposed that tackles both autism spectrum disorder detection and cognitive improvement. Specifically, the SA-ViT uses a transformer encoder, which accepts multimodal data including facial images, videos,

and behavioral records, and utilizes multiple-stage feature aggregation and Concentrate-and-Enhance self-attention to attain an accurate classification rate of 97.6% on the ASD Facial Image Dataset, surpassing classical CNN frameworks (91.2%) and typical vision transformers (94.8%).

Quantitative analysis shows that personalized cognitive tasks generated by SA-ViT contribute to significantly improved visual memory capacity (34.2%), pattern identification (28.7%), sustained attention (32.5%), and executive function (32.3%) after eight-week training sessions. Effect sizes (d=1.38-2.53) have been recorded for all four dimensions, representing some of the highest values ever obtained in studies on artificial intelligence–based cognitive training for autism. The incorporation of Grad-CAM enables clinically meaningful attention visualization, which correlates well with common ASD face attributes.

Some important findings have substantial implications on the use of our system for ASD detection and treatment:

Self-Attention Captures Distributed ASD Characteristics: The model's capability of capturing long-range interactions among distantly located facial regions seems to successfully identify distributed morphological patterns that go unnoticed by local filters in CNNs.

Diagnosis and Treatment are Compatible Objectives: The same learned representation can be used for both purposes – the high correlation between the learned attention maps and the behavioral measures (r=0.76) indicates that these learned representations contain clinically relevant features that predict treatment success.

Personalized Task Creation Facilitates Learning: Personalized approach to generating learning tasks, taking into account current user progress, resulted in significantly greater improvements in comparison with conventional treatments. It confirms the idea that personalized tasks suit ASD patients better than static tasks.

Model Explainability Increases Clinical Acceptance: Attention maps generated using Grad-CAM allow clinicians to verify the model's decisions, thus overcoming the main obstacle in deploying machine learning models in clinical practice.

First, limitations are the size of the dataset (2,500 images) compared to the complexity of the model used; a large scale and multi-center validation study needs to be done. The cognitive improvement assessment did not include any longitudinal assessments beyond 8 weeks. In addition, there is no inclusion of the neuroimaging modality (fMRI and sMRI).

Future studies will need to focus on different directions. Multi-center validation with different ethnic backgrounds and ages would allow generalization to other groups. Longitudinal assessment after one year (12 to 24 months) would help in identifying whether the cognitive improvements are sustained and generalized to real-world settings. Using neuroimaging modalities (fMRI and sMRI) could help in creating a more complete diagnostic tool since transformer architecture models have been used before for brain network connectivity. Real-time adaptive training systems using physiological parameters can be added for improved engagement.

In summary, it is evident that the SAD-ViT proves that transformers are not only useful for diagnosis but can also help in therapy. Combining all the aspects, including correct classification, personalization of cognitive tasks, and explanations of how the results were generated, opens new possibilities for AI to help people with autism.

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