Virtual Reality Technology for Early Detection and Diagnosis of Autism Spectrum Disorder

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Abstract

The presence of Autism Spectrum Disorder (ASD) in a person makes them lag in social interaction. Thus, early detection and diagnosis solutions are needed for ASD patients. Hence, in this paper, a Slice-wise Fixed Poly-logarithmic-based Adaptive Neuro-Fuzzy Inference System (SFP-ANFIS)-based Virtual Reality (VR) intervention for the early diagnosis of ASD is proposed. Initially, the Electroencephalogram (EEG) signal of an ASD patient is taken and pre-processed. Next, the features are extracted from the pre-processed output. Then, based on the extracted features, a Semi-Hausdroff-based K-Prototype Algorithm (SH-KPA) is utilized to group the patients with autism and their corresponding emotions. Similarly, from the behavioral images, the facial landmarking is done using the Tangent Steep-based Supervised Descent Method (TS-SDM). Next, the features are extracted after landmarking the facial points. Then, these extracted features along with the behavioral image data are classified by utilizing the SH-KPA technique. From the SH-KPA results of EEG signal and behavioral images, the similarity is estimated to recognize the ASD child's emotions. Then, based on the previous health records of patients, the state of the patient, estimated emotions, and similarity score, SFP-ANFIS is used to predict the level of ASD and recommends a possible solution to be conducted with a VR device. Hence, autism and emotion are detected with an accuracy of 97.45%, and the level of ASD is identified with a prediction rate of 97.12%, thus showing better performance than the existing works.

Keywords:

Autism Spectrum Disorder (ASD); Virtual Reality (VR); Electroencephalogram (EEG); Semi-Hausdroff-based K-Prototype Algorithm (SH-KPA); ASD solution recommendation.

Highlights:

- A novel approach using Sequential Hybrid Kohonen's Self-Organizing Feature Map - Adaptive Neuro-Fuzzy Inference System within a virtual reality framework is proposed for early ASD diagnosis.
- The model integrates EEG signals and behavioral images to capture both physiological and behavioral aspects of ASD, enhancing the diagnostic accuracy.
- Features are extracted from EEG signals and facial landmarks, then classified using SH-KPA (Sequential Hybrid Kohonen's Self-Organizing Feature Map) to group ASD patients and identify associated emotions.
- The model predicts ASD severity levels and recommends tailored interventions.
- The proposed model demonstrates as an effective tool for early ASD detection and intervention using VR technology.

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1. Introduction

In recent days, many children have a neurodevelopmental disorder, such as cerebral palsy, intellectual disability, or ASD (Hadders-Algra 2021). However, the occurrence of ASD causes damage to the neighbor members due to their aggressive behaviors. Thus, ASD assessment is particularly important and may have long-term benefits in the lives of ASD people (Kollias et al. 2021). ASD is a state referring to a neurological abnormality that affects normal development and leaves an impact on a person (Karim et al. 2021) (Raj and Masood 2020). Teenagers and adolescents with ASD focus less on socially relevant features like faces and have been reported to avoid eye contact and instead focus more often on the mouth area (Roth et al. 2020). Also, ASD appears in childhood, often before the age of three (Ismail et al. 2020). Individuals with ASD also display a spectrum of symptoms, including anxiety disorders, sleep disturbances, attentional disorders, and intellectual disabilities in addition to these core behavioral deficits (Kelly et al. 2021). In spite of the fact that there is no cure for autism spectrum disorder, early detection can teach children a variety of skills, such as communication and socialization, as well as control their repetitive behaviors (Baranwal and Vanitha 2020) (Popescu and Popescu 2020). Traditionally, ASD detection was performed based on encountering a new clinician in a new environment (Kohli et al. 2022). In spite of their accuracy, these methods are undoubtedly exhaustive and extensive (Subah et al. 2021) and also cause discomfort to patients due to social pressure. To solve this problem, computer-aided models are developed. Computer-based interventions, such as VR technology seem to have given reliable diagnostic results, given the economic costs, children's fascination with technology, and easy wide-ranging access (Akhtar and Feeney 2020). CNN based on neuroimaging approaches is the most widely used computer-aided ASD diagnosis method (Alam et al. 2022). However, the existing models could not provide reliable results for a single type of input data, which lacks reliability. Thus, this paper proposes a novel SFP-ANFIS-based VR intervention for ASD diagnosis by combining EEG signals and behavioral image data. This model improves the accuracy and prediction rate by providing personalized recommendations without clinician involvement.

1.1. Problem Statement

The recognized problems in the existing works are:

- Individuals with ASD face challenges like expressing their inner thoughts. Thus, the analysis of autism solely on the behavioral image could not be accurate. Also, the correlation of EEG signals could be difficult in determining autism in children. Thus, in real-time, the level of ASD could not be predicted accurately using the behavior analysis or brain functional analysis alone as ASD patients could not represent the actions they think.
- Rarely, works were focused on recommending a solution for ASD patients without clinician involvement. These data might be limited, which leads to inaccurate detection of ASD.
- The recognition and processing of emotions is a crucial part of the identification of autism in children precisely. The existing works did not concentrate on emotion recognition in the diagnosis of ASD based on functional brain data, which affects the overall performance of the model.

By considering these problems, the proposed works' contributions are:

- To improve the accuracy of the proposed system in the analysis of ASD, the EEG signal that provides insights into brain activity and behavioral image data that captures external expressions and actions are used for ASD-level prediction in SFP-ANFIS.
- To avoid clinician involvement, the VR technology-based ASD diagnosis solution recommendation with SFP-ANFIS is proposed. Thus, the reliance on clinical data is avoided, thus improving the diagnosis of ASD.
- To recommend an efficient solution regarding autism detection, the input is pre-processed, and the facial landmarking of the image is done using the TS-SDM model. Then, the emotions with autism are based on the SH-KPA for effective diagnosis of ASD.

The remaining format of this paper; Section 2 describes the related works. Sections 3 and 4 elaborate on the proposed approaches and the corresponding results. Section 5 concludes this paper.

2. Related Works

(Bilgen et al. 2020) recommended Cortical Morphological Networks (CMN) for the application of autism diagnosis. The CMN derived from conventional T1-weighted Magnetic Resonance Imaging (MRI) was used for autism detection. The results revealed a higher performance of the developed model. But, without hyper-parameter optimization, the CMN model was limited to some extent.

(Gao et al. 2021) presented a unified framework for early-stage status prediction of autism. The developed model introduced a segmentation and parcellation map for ASD prediction. The results revealed higher performance for the presented model. But, the model could possess an overfitting problem due to data insufficiency.

(Negin et al. 2021) developed a model for vision-assisted recognition for the early diagnosis of ASD. The ASD-associated behaviors were recognized based on the Long-Short-Term-Memory. The results revealed that an action-recognition-based system assisted in the timely diagnosis of ASD. However, the skeleton obtained in the developed model was not reliable to make robust predictions.

(Raya et al. 2020) introduced ML and VR on body movement behavior to classify children with ASD. The VR technology was used for the classification of behavioral biomarkers. The results revealed that the prediction of biomarkers improved the ASD diagnosis. Yet, without counterbalancing the stimuli conditions, the children's function could not be recognized perfectly.

(Saranya and Anandan 2022) implemented a hybrid DL algorithm to predict ASD. The model integrated a fuzzy Extreme Learning Machine for ASD diagnosis. The model revealed that the implemented model attained better accuracy. Still, due to the random initialization of the parameters, the model robustness was reduced.

(Mazumdar et al. 2021) investigated the visual exploration of images for the early detection of children with ASD. The combined use of ML and eye-tracking information was used for ASD detection. The results revealed that the developed model identified children with developing ASD. The model neglected the fixations unattractive to ASD patients, which could increase the false negatives.

(Ahmed et al. 2022) introduced eye-tracking-based diagnosis and early detection of ASD based on ML and DL techniques. CNN and SVM were utilized for the feature map extraction and classification. The high diagnostic ability of the model was proven in the experimental analysis. Yet, with the CNN for feature extraction, the positional features were missed, which deteriorated the performance of the model.

(Awaji et al. 2023) established facial feature image analysis for ASD diagnosis based on Convolutional Neural Network (CNN). Here, the facial images of children were taken and preprocessed for noise removal and normalization. Then, the features were extracted from the pre-processed image and classified using CNN. Thus, the autism was detected accurately. Yet, focusing only on the facial image might miss important information and lead to an improper autism diagnosis.

(Xu et al. 2024) developed ASD diagnosis with EEG signals using brain functional connectivity and the combined CNN and Long Short Term Memory (LSTM). Initially, the EEG signals were pre-processed, and the connection matrix calculation was done. Next, from the matrix, the features were extracted and augmented. Finally, the ASD was identified using the combined CNN and LSTM classifier. Hence, the autism was detected efficiently. On the contrary, the combination of the classifier might perturbate the input data and cause misclassification of ASD.

(Reddy and Andrew 2024) presented ASD diagnosis in children using a deep learning model by using facial features. First, the image data was collected and aggregated. Then, the image was preprocessed, and the ASD was detected using EfficientNet, which accurately predicts autism in children. Thus, the presence of autism was detected precisely. But, the capturing of important features using EfficientNet was difficult, which reduced the performance of the model.

(Banire et al. 2024) accomplished autism detection using machine learning regarding the behavioral image of children. Here, the image data was collected, and the noise was removed from the image. Then, the facial behaviors were marked, and the important facial features were extracted. Finally, using the attention model, the presence of autism was detected effectively. However, the emotions were not recognized by the model, which affected the autism diagnosis.

(Zhou et al. 2024) demonstrated gaze patterns in children for ASD diagnosis using emotional images. Initially, the image was taken, and the Dynamic Time Wrapping elimination was done to select the important data. Then, by using the facial features, the ASD was classified using the LSTM classifier. Thus, the ASD was identified more accurately. Yet, brain activity was not considered, which reduced the prediction of autism in children.

Summary of related works

The existing works concentrated on the detection of ASD by using the facial images of children or by using the EEG signals, but not with both. As the traditional model missed either the brain activity of the children or the facial features, the ASD diagnosis was not effective in the existing models. In the proposed method, the ASD diagnosis is done based on the EEG signals and the behavioral image of the children. In the prevailing works, the clinical data was taken for diagnosis purposes. Relying only on the limited clinical data resulted in low accuracy in determining autism in children. In the proposed model, the VR technology-based diagnosis is done. In some of the related works, the emotions, which play an important role in autism detection, were not concentrated. This reduced the overall classification result in autism diagnosis, whereas this limitation is avoided by detecting the emotion from the behavioral image and EEG signals in the proposed framework.

3. Proposed ASD Detection and Diagnosis Methodology

In the proposed work, emotion and autism are detected using the SH-KPA technique, and the autism level is identified by utilizing the SFP-ANFIS method regarding the behavioral images and EEG signals of children. Here, the behavioral image and the EEG signals are pre-processed. The pre-processing helps in detecting ASD accurately. Then, the facial expressions are landmarked in the pre-processed image by using the TS-SDM method. Next, the presence or absence of autism and the respective emotions are detected with the help of the SH-KPA technique. Finally, by utilizing the autism-detected emotion and previous health records, the level of autism is detected by the SFP-ANFIS technique. An SFP-ANFIS-based VR intervention model is proposed, and the block diagram and the flowchart of the proposed framework are illustrated in Figure 1 and Figure 2, respectively.

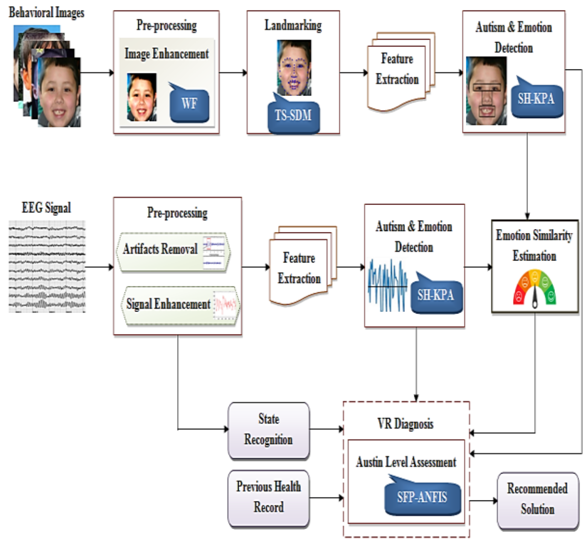


Figure 1. Proposed Architecture

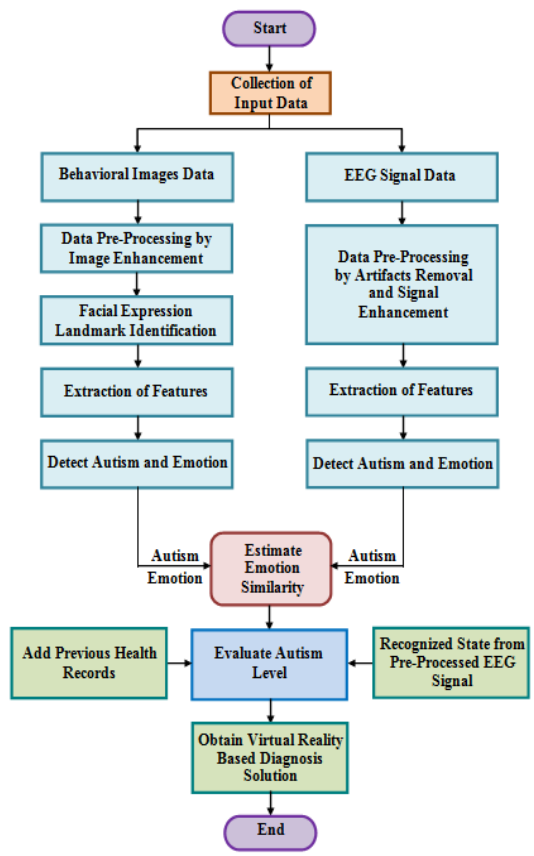


Figure 2. Flowchart of the Proposed Framework

3.1. Pre-processing with EEG Data

Initially, the historical EEG data of ASD children with emotions are taken and pre-processed with artifact removal and signal enhancement based on the sparseness. Thus, the pre-processed data is given as:

$$P_n = \{P_1, P_2, ..., P_\alpha\} \tag{1}$$

Where, P_α depicts the α^{th} pre-processed patients' EEG data.

3.2. Autism and emotion recognition

In this phase, from the pre-processed EEG data, the ASD-diseased patients' data with their corresponding emotions and non-ASD data are grouped and detected separately using the SH-KPA method regarding the extracted mean, variance, and entropy features (B_n). Here, the K-Protocol Algorithm (KPA), which is fast, robust, and intuitive, is selected due to its ability to group based on data similarity. But, the dissimilarity assessment between the categorical data and its cluster center could not provide accurate clustering. Thus, the Semi-Hausdroff-based dissimilarity is introduced in KPA. Initially, $\kappa -$ cluster centres are randomly initialized in SH-KPA. The initialized centroids of categorical $(\Im_q^{str})$ and numerical $(\Im_q^{data})$ data are given as:

$$\Im_q = \{\Im_q^{data}, \Im_q^{str}\} \tag{2}$$

Here, the categorical data represents the qualitative data, which can be split into categories, such as response, gender, and so on. Also, the numerical data is the mean, variance, and entropy of the EEG signal. This categorical and numerical data helps in labeling the data into the required class. After the centroids selection, the distance (Γ) between $\Im_q^{data}$ and the numerical data points $(w_m \in B_n)$ is estimated as:

$$\Gamma_{q,m} = \sqrt{\sum_\ell \left(\Im_q^{data} - \overline{w}_m\right)^2} \tag{3}$$

Where, $\overline{w}_m$ represents the mean value of the total numerical data points (ℓ). This distance helps in clustering/grouping the data points regarding the similarity between the points. Then, the dissimilarity (Ω) between categorical data $(\hbar_m \in B_n)$ and its centroid is estimated to handle the mixed type of data using the SH tec hnique as:

$$\Omega_{q,m} = \max\left[di\left(\Im_q^{str} - \hbar_m\right)\right] \tag{4}$$

Here, the dissimilarity matrix is depicted as $di\left(\Im_q^{str} - \hbar_m\right)$. Finally, calculate $\Gamma_{q,m} + \Omega_{q,m}$ with every $\kappa -$ cluster and assign the object to a cluster that contains a low difference. The clustering is done until the convergence of all the data points is completed regarding the minimum distance and dissimilarity of the data points. Thus, the final cluster obtained is denoted as:

$$\lambda_\kappa = \left[\lambda_c^{em}, \lambda_f^{em}\right] \tag{5}$$

Where, $\lambda_c^{em}, \lambda_f^{em}$ depicts the data in autism (c) and non-autism (f) classes with their corresponding emotion (em). The pseudocode of SH-KPA is:

Input: EEG features (B_n)

Output: Grouped data

Begin

Initialize B_n cluster centers $\Im_q^{data}, \Im_q^{str}$
For each w_m do
Estimate similarity distance $\Gamma_{q,m}$
Estimate $\Omega_{q,m}$ with SH
If $((\Gamma_{q,m} + \Omega_{q,m}) == high)$ {
Repeat For
} **Else** {
Assign w_m to λ_κ
}
End If
End For
Return $\lambda_c^{em}, \lambda_f^{em}$

End

3.3. Processing with behavioral images

Meanwhile, the ASD children's behavioral images dataset and the emotion images are taken and pre-processed for image enhancement using a Wiener Filter (WF). Thus, the pre-processed images are given as:

$$I_h = \{I_1, I_2, ..., I_r\} \tag{6}$$

3.4. Landmarks identification

Then, in I_h, the landmarks of the facial expressions are created for effective feature extraction based on the Tangent Steep-based Supervised Descent Method

(TS-SDM). Here, the SDM is selected due to its landmarking ability. But, it could not mark the descent gradients in the image. Thus, the TS technique is utilized in SDM.

Initially, with I_h and initial configuration of face landmarks (l_0), the face alignment has been done by matching the initial shape close to the correct shape $(l^{\bullet})$ of the face. For this, the shape increment (i) is updated to minimize the optimization function $(O(\ ))$ as:

$$O(l_0 + i) = \left\| \beta_{ex}\left(I_h\left(l_0 + i\right)\right) - \beta_{ex}\left(I_h\left(l^{\bullet}\right)\right) \right\|^2 \quad (7)$$

Where, β_{ex} denotes the feature extraction function. Then, to generate the sequence of updates from (l_0) that matches the $(l^{\bullet})$, TS-SDM learns a series of descent directions and re-scaling factors based on the Taylor expansion as:

$$O(l_0 + i) \approx O(l_0) + \Im_O(l_0)^T i + \frac{1}{2} i^T \lambda(l_0) i \quad (8)$$

Where, $\Im_O, \lambda$ are the Jacobian and Hessian matrices evaluated at (l_0). The update for (c) is derived using the TS method as:

$$i_1 = \frac{\partial \beta_{ex}\left(I_h\left(c^{\bullet}\right)\right)}{\partial B} G \quad (9)$$

Where, G depicts the tangent vector chosen to steep gradient direction, and B depicts the bias. Then, the shape update in each iteration (I) can be calculated as:

$$l_{\mathrm{I}} = l_{\mathrm{I}-1} + G_{\mathrm{I}-1}\beta_{ex}\left(I_h\left(l_{\mathrm{I}-1} + i\right)\right) + \varepsilon_{\mathrm{I}-1} \quad (10)$$

Hence, ε are learning parameters to give the output as:

$$Q_h^p = \arg\min_{G_{\mathrm{I}}, \varepsilon_{\mathrm{I}}} \sum_{Q_h} \sum_{l_{\mathrm{I},p}} \left\| i^{\bullet}_{\mathrm{I},p} - G_{\mathrm{I}}\beta_{ex}\left(I_h\left(l_{\mathrm{I},p} + i\right)\right) - \varepsilon_{\mathrm{I}} \right\|^2 \quad (11)$$

Where, Q_h^p denotes the output image with p number of landmarks.

Recognition of the autism and corresponding emotions: After the landmarked image is obtained, the neighborhood's different features, SIFT, and Bi-WooF features are extracted. Then, based on the extracted features, the autism patients' image data, and their corresponding emotions are separated from the non-autism patients' data using the SH-KPA technique. The output is depicted as:

$$\gamma_j = \left[\gamma_c^{em}, \gamma_f^{em}\right] \quad (12)$$

Where, $\gamma_c^{em}, \gamma_f^{em}$ depicts the grouped results based on images of autism (γ_c) and non-autism (γ_c) based on their emotion.

3.5. Emotion Similarity Estimation

After the recognition of the autism in the patients with their emotions in the EEG and behavioral data, the similarity score of the emotions is estimated to diagnose the autism as the ASD-affected children could not represent the actions they think. The similarity (S) is estimated as:

$$S = \frac{\gamma_c^{em} . \lambda_c^{em}}{\left\|\gamma_c^{em}\right\| . \left\|\lambda_c^{em}\right\|} \quad (13)$$

This S value is used to recommend the diagnosis for the ASD patient.

3.6. VR-based diagnosis

After an ASD person is detected, the VR-based diagnosis recommendation model is developed to avoid the intervention of clinicians. The purpose of this diagnosis is that the data points can be tracked effectively and the patients can achieve the required diagnosis result without any doctor's consultation. Also, the diagnosis can be made more accurately than other diagnosis methods. Here, the recommendation is created after the risk analysis by the Slice-wise Fixed Poly-logarithmic-based Adaptive Neuro-Fuzzy Inference System (SFP-ANFIS). Here, the ANFIS is selected as it was efficient for the risk assessment based on the fuzzy rules. But, the tunable consequent parameters caused parameter complexity. Thus, to solve this problem, the SFP is introduced in ANFIS. The process of Virtual reality-based diagnosis of autism is explained below.

Initially, in the fuzzification layer, typical rules set with fuzzy if-then rules are created to formulate the conditional statements that are used for ASD diagnosis. The if-then rule is described below.

If be is mil **and** sc is mil , **and** $lan = mil$ **then** $asd = low$
If be is sev **and** sc is mil , **and** lan is mod **then** $asd = medium$
If be is sev **and** lan is sev **then** $asd = high$

Where, be, lan, sc depict the crisp inputs, such as behavior, language, and social skills of the ASD patient, and mil, mod, sev depict the stages of the patients, such as mild, moderate, and severe. The condition states that if the behavior, social skills, and language are at a mild level, then the ASD is low. Also, if the behavior is severe, social skills are mild, and the language is moderate, then the ASD is medium. And, if the behavior and language are severe, then the ASD is high. Thus, based on these rules, the five layers of SFP-ANFIS are processed. The fuzzification is done to identify the degree of relation between the input data as follows.

$$F_1(c) = \nabla\left(\gamma_c^{em}(cr), \lambda_c^{em}(cr)\right) \tag{14}$$

Where, $F_1(c)$ is the fuzzified output, cr is the crisp input, and ∇ are the bell-shaped membership functions. The second layer is the rule layer, which generates the output rules as:

$$\Psi_c = \nabla(\gamma_c) * \nabla(\lambda_c) \tag{15}$$

Where, Ψ denotes the output of the nodes in the second layer that gives the firing strength of a rule. The third layer (ϖ_c) performs the normalization of Ψ_c, and output is depicted as Ψ_c^{nr}. The normalization is done to analyze the fuzzified data and the membership function along with the rules set to determine the required output. In the fourth layer, the Ψ_c^{nr} is in product with the weight parameters to form the output.

$$\varpi_c = \Psi_c^{nr} \times \eta_c \tag{16}$$

Where, η_c denotes the consequent parameter set, which is kept constant using the SFP system as:

$$\eta_c = y(c).\log(b) \tag{17}$$

Here, y, b depict the computable function and number of nodes in layer four. Finally, the fifth layer has a single fixed node in which all the defuzzied inputs from the previous layer are summated as:

$$\tau_{out} = \sum_c \Psi_c^{nr} \eta_c \tag{18}$$

Where, τ_{out} depicts the output autism level (i.e., severe, high, or medium).

Then, the SFP-ANFIS is again trained to produce the diagnosis recommendation based on the previous history (ph), ASD level (Al), state (st), and emotional similarity (es). Some of the rules generated based on these inputs are given as:

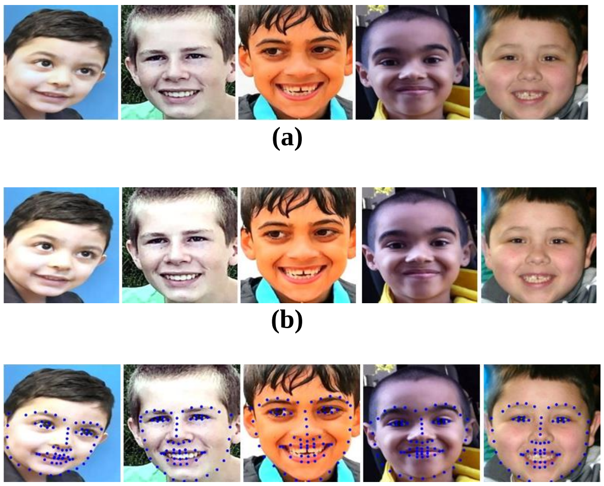
If ph is nil **and** es is 1 **and** Al is low **and** st is act **Then** VRD is s_1
If ph is ch **and** es is <1 **and** Al is $mild$ **and** st is act **Then** VRD is s_2
If $es < 0.5$ **Then** VRD is s_3

Where, nil, ch depict no ph and congenital heart disease, respectively, act depicts the active state, and s_1, s_2, s_3 depict the solution to be recommended in the VR device VRD. The rule states that when the previous history is nil, the emotional similarity is one, the ASD level is low, and the state is active, then the solution 1 diagnosis is made. Also, when the previous history had heart disease with emotion similarity below one and with mild ASD level and active state, then the solution 2 diagnosis is recommended. Also, when the emotional similarity is lower than 0.5, solution r is recommended using the VR diagnosis model.

Similar to the above rules, more rules are generated for the sleeping and drowsy state of ASD patients. Therefore, based on these rules in the SFP-ANFIS, the optimal VRD diagnosis recommendation (μ_{out}) that provides the diagnosis recommendation solution is provided. Thus, the intervention of outside clinicians and the discomfort of ASD patients can be mitigated using this system.

4. Result and Discussions

In this section, the experimental results of the proposed approaches are discussed. The experiments are performed on the working platform of Python with the collected data from publicly available sources. The sample image results are given in Figure 3.



(a)

(b)

(c)

Figure 3. Sample images of (a) Input (b) image enhanced and (c) land marked images

4.1 Dataset Description

The performance of the proposed work is done by collecting the behavioral image data from the ASD children's behavioral images dataset and the link is given in the reference section. This dataset consists of a total of 1470 images of the autistic class and 1470 images of the non-autistic class. From these images, for each class, 80% of the images i.e. 1176 images are used for training and 20% of the images i.e. 294 images are utilized for testing purposes. Also, the EEG signals are collected from publicly available sources, and for each class, 1470 EEG data were taken. Out of these, for each class, 80% of the data is used for training and 20% data is used for testing.

4.2 Performance Analysis

Here, the performances of the proposed algorithms, such as SFP-ANFIS, SH-KPA, and TS-SDM are proved based on experimental analysis with conventional techniques.

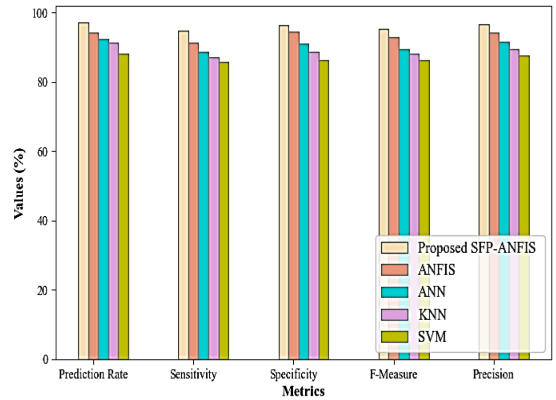


Figure 4. Qualitative analysis of SFP-ANFIS

In Figure 4, the ANFIS gives quality results than the other conventional methods for the prediction rate, precision, sensitivity, F-Measure, and specificity values. But, with the given fuzzy rules and the SFP technique, the SFP-ANFIS increased the quality of prediction rate, F-Measure, and specificity values to 97.12%, 95.26%, and 96.42%, respectively. In the proposed model, the state of the EEG signal, the previous clinical history, and the emotion of the autism patient were given to diagnose the ASD. This shows that with the proposed SFP-ANFIS, the autism level prediction is done with more quality; thus, the solution recommendation quality is also increased.

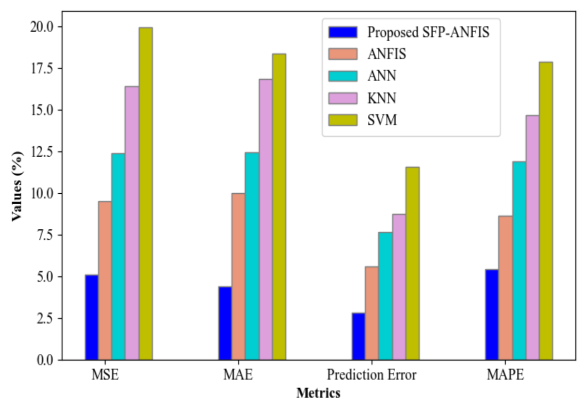


Figure 5. Error analysis

Figure 5 reveals that the proposed SFP-ANFIS attained less error than the baseline ANFIS, Artificial Neural Network (ANN), K-Nearest Neighbors (KNN), and Support Vector Machine (SVM). The SFP-ANFIS attained a Mean Absolute error (MAE), Mean Squared Error (MSE), and Mean Absolute Percentage Error (MAPE) of 4.42%, 5.13%, and 5.43%. Here, the Slice-wise Fixed Poly-logarithm was used to solve the tuning problem in the proposed method. This shows that the proposed model gave a more reliable solution recommendation than the existing techniques.

Table 1: Time analysis of SFP-ANFIS

Techniques	Prediction Time (ms)
Proposed SFP-ANFIS	3674
ANFIS	4879
ANN	5274
KNN	7371
SVM	9456

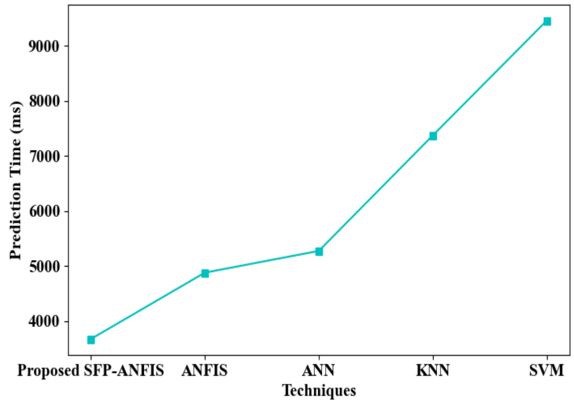


Figure 6. Graphical Representation of SFP-ANFIS

Table 1 and Figure 6 depict that the time taken to execute SFP-ANFIS is much less than the time taken to execute the ANFIS, ANN, KNN, and SVM. The diagnosis was done by the proposed framework based on the Virtual Reality diagnosis. This indicates the better time efficiency of the proposed model for the risk level prediction and the diagnosis solution recommendation.

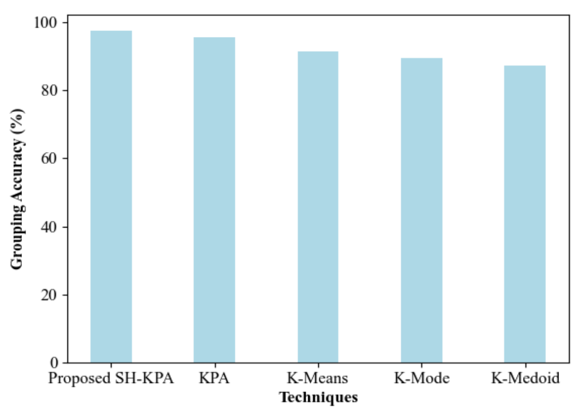


Figure 7. Grouping accuracy

Figure 7 reveals that the grouping accuracy of the KPA was higher than the other grouping techniques. But, the SH-KPA grouped the autism and non-autism patients' data with their emotions 1.81% more accurately than the KPA technique. As the dissimilarity was found by the SH dissimilarity technique, the limitation present in the proposed method was avoided. This proves the suitability of the SH-KPA for ASD detection in the proposed framework.

Table 2: Time analysis for recognition of ASD

Techniques	Grouping time (ms)
Proposed SH-KPA	861
KPA	1033
K-Means	1337
K-Mode	1673
K-Medoid	2071

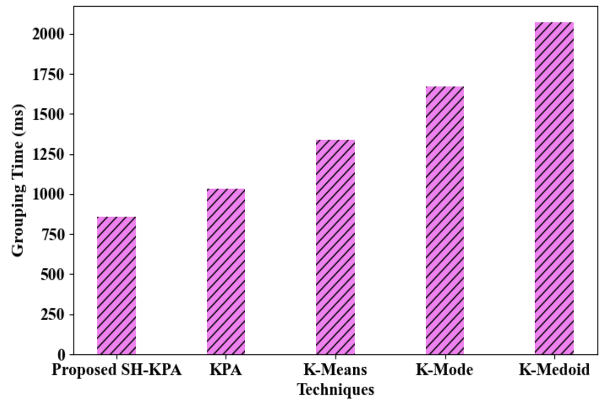


Figure 8. Graphical Comparison regarding recognition of ASD

Table 2 and Figure 8 show that the K-Medoid takes more time to group the data, which is less suitable for the proposed model. But, the SH-KPA takes less time to group a large amount of input EEG and image data, which proved the suitability of SH-KPA means for the proposed ASD diagnosis detection model. This is because the EEG signals and the behavioral images were preprocessed, and then the features were extracted. Also, in the proposed model, the finding of dissimilarity by the SH technique enhanced the performance of the proposed framework better than the existing models.

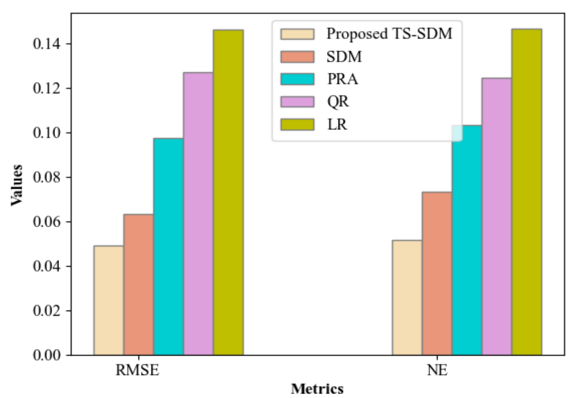


Figure 9. Error analysis of landmarking

The least Root Mean Square Error (RMSE) of 0.0491 and Normalized Error (NE) of 0.0516 obtained by the proposed TS-SDM are proven in Figure 9. But, the prevailing SDM, Principle Regression Analysis (PRA), Quadratic Regression (QR), and Linear Regression (LR) attained higher error values than the TS-SDM. The descent gradients in the image were calculated by the Tangent Steep calculation in the proposed technique. Thus, it is verified that TS-SDM is reliable for landmarking in the proposed model.

Table 3: Success rate analysis

Techniques	Success rate (%)
TS-SDM	94.34
SDM	91.94
PRA	86.43
QR	83.46
LR	81.04

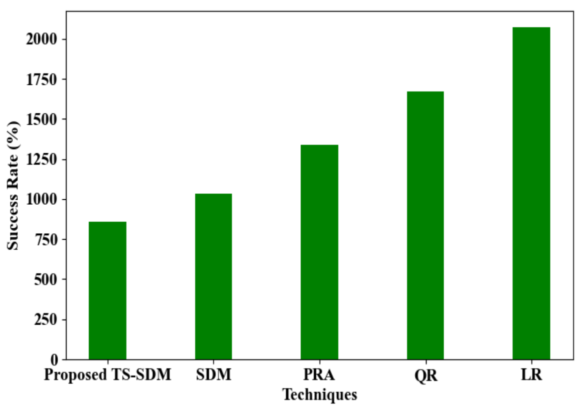


Figure 10. Graphical Comparison of TS-SDM

The success rate of facial landmarking by the proposed and baseline techniques is unveiled in Table 3 and Figure 10. The criteria for success rate is the intervention met by the proposed method regarding landmarking the facial points in the pre-processed image effectively. The success rate is evaluated based on the number of successful landmarking to the total number of landmarking evaluated.

Here, the success rate of SDM in landmarking is higher, followed by the PRA technique. But, the TS-SDM attained a higher success rate than the SDM technique, which makes it more suitable for landmarking in the proposed model. Thus, the calculation of gradient using the TS technique improved the performance of the proposed framework regarding facial landmarking.

4.3 Comparative analysis

In this section, the comparative analysis of the proposed and the existing models as given in Table 4 are analyzed in this segment.

Table 4: Comparative analysis regarding related works

Models	Efficiency (%)
Proposed SFP-ANFIS	97.12
(Negin et al. 2021)	79
(Raya et al. 2020)	89.36
(Mazumdar et al. 2021)	88.5

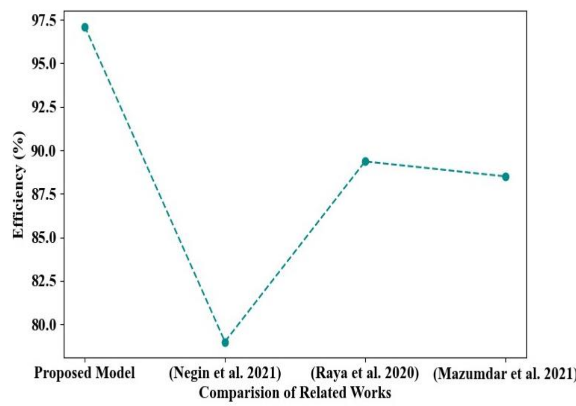


Figure 11. Graphical Comparison regarding related works

The efficiency based on autism detection is unveiled in Table 4 and Figure 11. The efficiency, which is the prediction rate, is the measure of how accurately the model has predicted the diagnosis of ASD. This efficiency is calculated by summing the true positive and true negative diagnoses of ASD and dividing it by the total number of diagnoses that are made. Here, even with the diagnosis solution recommendation, the proposed model attained 18.12%, 7.76%, and 8.62% higher efficiency than the (Negin et al. 2021), (Raya et al. 2020), and (Mazumdar et al. 2021) models. This shows the superiority of the proposed model over the existing models in ASD prediction.

5. Conclusion

This paper proposes an SH-KPA-based ASD prediction and SFP-ANFIS-based diagnosis solution recommendation in VR devices. The results of the proposed algorithms are experimentally analyzed and discussed. Here, the behavioral images and the EEG signals are taken and preprocessed. Then, from the pre-processed image, the facial landmarking is done using the TS-SDM technique with a success rate of 94.34%. Then, from the pre-processed EEG signals and the landmarked images, the features are extracted. Next, by using the SK-KPA technique, ASD with emotions is recognized with a clustering accuracy of 97.45% and grouping time of 861ms. The experimental analysis revealed that the SFP-ANFIS gave quality results by attaining a 97.12% prediction rate with less time of 3674ms. Finally, by utilizing the SFP-ANFIS method, the autism level assessment is done with respect to VR diagnosis with a prediction time of 3674ms and a prediction rate of 97.12%. Thus, it is concluded that the proposed model effectively recognized ASD and diagnosed the autism level regarding the EEG signal and behavioral image of the children.

Future Recommendation

Although the proposed model detected ASD efficiently, this work neglected the occurrence of comorbid disease in ASD patients. Thus, in the future, ASD and other comorbid neurological diseases will be differentiated to accurately detect ASD and further improve the performance of the proposed model.

Conflict of Interest

None

References

Dataset link: https://www.kaggle.com/datasets/cihan063/autism-image-data

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