International Journal of Engineering Trends and Technology
ISSN: 2231-5381/ https://doi.org/10.14445/22315381/IJETT-V74I6P110
Volume 74 Issue 6, 140-156, June 2026

Research Paper

Optimized Pre-trained Feature Selection with Support Vector Machine Model For Autism Spectrum Disorder Detection

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Received: 08 October 2025 Revised: 01 April 2026 Accepted: 20 April 2026 Published: 27 June 2026

Abstract *- Autism Spectrum Disorder (ASD) is associated with a nervous system development condition identified by persistent challenges in social communication and behavior, typically identified in the formative years. It is associated with repetitive behaviours and difficulties in social interaction among affected beings. Various approaches to autism spectrum disorder classification have been developed, comprising emotional tests, facial image analysis, and neuroimaging techniques. ASD is a challenging task to diagnose through medical analysis, and some tests are time-consuming and more expensive. In this research article, a novel approach with an Optimized Pre-Trained Feature Selection With Support Vector Machine (OPFSVM) detection model for ASD is proposed to overcome the existing challenges and problems. The novel method accurately identifies Autism in children; this study employed a pre-trained ResNet50 feature extraction method. The feature selection process is performed using a Particle Swarm Optimization (PSO)approach that helps improve system performance by eliminating irrelevant feature sets while retaining the most significant ones. Subsequently, the Support Vector Machine (SVM) model is applied to perform two-class classification of ASD. The proposed (OPFSVM) model integrates pretrained feature extraction and optimized feature processing in the SVM model with binary classification to accurately detect Autism in children. For training the proposed model, an online accessible dataset is used, including facial images for kids, analyzed with Autism, and control subjects categorized as either autistic or non-autistic. According to the outcomes, the suggested OPFSVM model is achieving 97% accuracy, 97% precision, and reducing the 3% error rate, compared with other methods (Vgg19, ResNet50, MobileNet, etc.). These findings highlight the implemented method's high effectiveness in early ASD detection and position it as an effective tool for timely and rapid analysis.*

Keywords *- Artificial Intelligence, Autism Spectrum Disorder, Machine Learning, Particle Swarm Optimization, Optimized Pretrained Feature Selection with Svm, Support Vector Machine.*

1. Introduction

Autism Spectrum Disorder (ASD) represents a condition affecting neurodevelopment that is lifelong and is marked by ongoing challenges in social and communicative interactions, along with the occurrence of recurrent and limited behavioral patterns. ASD presents itself at an early age and is highly heterogeneous in the severity of symptoms, cognitive level, and behavioural patterns, which makes it more difficult to diagnose and plan interventions. During the past several years, ASD has received an expanding interest because of its growing prevalence and the high clinical, social, and economic cost it places on those affected, their families, and healthcare systems.

ASD is one among several significant global medical issues affecting mental well-being. Recent works emphasise the increased use of AI, ML, and DL methods to enhance the diagnostic accuracy and decision-making in mental healthcare [1, 3]. The models of AI are especially useful at detecting complex, non-linear patterns in large-scale and high-dimensional data, which cannot always be interpreted using conventional clinical evaluations. Consequently, AI-based diagnostic systems are currently being considered as auxiliary devices to aid in early screening and risk detection in neurodevelopmental disorders, including ASD.

The epidemiological data show that the prevalence of ASD is steadily growing, particularly in children of developed nations. Population-based surveys on ASD have found significant differences in prevalence rates according to socio-demographic variables, co-morbidities, and access to healthcare services [4]. Besides the clinical issues, ASD has a pronounced influence on the quality of life of caregivers, which can manifest itself in increased psychological stress, emotional load, and decreased social well-being [2]. These issues highlight the need to have early and effective detection methods that may minimise the delays in diagnosis and enable prompt intervention [5].

The conventional method of ASD diagnosis is based on behavioural observation, interviewing with caregivers, and standardised psychological tests. These approaches are subjective, time-consuming, and necessitate professional skills, which might not be easily available in all clinical or geographical locations despite being effective [6, 7]. Therefore, there is a growing need for objective, automated, and cost-effective screening tools that can be used to supplement the current diagnostic processes.

The latest developments in DL and ML have shown promising outcomes in the detection of ASD based on various data modalities, such as behavioural data, neuroimaging, and facial images [8, 9]. In a research study, investigators at the University of Missouri [10] investigated the possibility of facial traits as diagnostic features of Autism in children. The learning implies that children with ASD have dissimilar facial features that make them stand out from the crowd of neurotypical children. These features contain a broader upper face with extensively spaced eyes and a comparatively smaller midface area, encompassing the nose and cheeks.

Fig. 1 Children with Autism and Non-Autism [11]

Figure 1, derived from the Kaggle record [11], illustrates the variations in facial feature patterns between the two cohorts: the 1st row shows a neurotypical (non-autistic) child, and 2nd row depicts a child with Autism. Analysis of ASD using facial characteristics is quickly advancing, mainly due to its consequences for emerging countries. Both children with ASD and naturally emerging children can benefit from Deep Learning (DL) approaches as a screening tool for ASD detection at an early time.

Facial image analysis, in particular, has emerged as a non-invasive and scalable approach, as subtle facial morphological differences between autistic and neurotypical children can be captured and analyzed using computer vision techniques. CNNs and Transfer learning-based methods have shown good capability in extracting discriminative features from facial images [12]. Nevertheless, most of the current methods have the disadvantage of being computationally intensive, having redundant feature representations, and poor generalisation capabilities when used on real-world data.

1.1. Novelty of the Proposed Work

The originality of the proposed study is that the Optimised Pre-trained Feature Selection with Support Vector Machine (OPFSVM) framework of early ASD detection with facial images is developed. The proposed method fuses three complementary elements, including pre-trained deep feature extraction, meta-heuristic feature optimization, and robust machine learning classification, unlike current methods that only use deep learning classifiers or conventional machine learning models.

To obtain high-level and discriminative facial features, a pre-trained ResNet50 architecture is applied with the help of transfer learning, which does not require a large amount of training on its own. Particle Swarm Optimization (PSO) is used to overcome feature redundancy and high dimensionality through a wrapper-based feature selection mechanism to ensure that only the most informative features are used in classification. Lastly, an SVM classifier is applied to carry out effective and dependable two-class classification, distinguishing autistic and non-autistic individuals.

This hybrid optimization-based paradigm is more accurate in classification, less computationally intensive, and more generalizable, unlike the traditional ASD detection models.

1.2. Problem Statement

Although there have been massive breakthroughs in the field of AI-based ASD detection, there are various limitations to the existing methods. Numerous deep learning models consist of many parameters that make them more expensive to compute, require more time to train, and are prone to overfitting, particularly in limited-size and diverse datasets. On the other hand, conventional machine learning methods do not always have the representational power to identify subtle facial features that could be applied to ASD.

Moreover, a number of studies conducted have neglected the use of feature selection, and their classifications have redundant or irrelevant features, which worsen the performance of the classification. Lack of optimization schemes and hybrid learning schemes restricts the scalability, interpretability, and reliability of existing ASD detection systems.

Hence, a profoundly necessary innovative, hybrid framework that is effective in integrating deep feature extraction with intelligent feature selection and powerful classification to enhance the accuracy of early ASD detection with reduced computational cost is urgently needed.

1.3. Motivation

The main driving force behind this research is the rising incidence of ASD and the urgency in finding early, accurate, and accessible diagnostic support tools. Early identification of ASD is important for the initiation of appropriate interventions, which can greatly influence cognitive development, social daily functioning, and general well-being for children with ASD.

Moreover, ASD imposes a lot of emotional and mental burden on caregivers that frequently leads to stress, anxiety, and lowered quality of life [2]. The delay in diagnosis, the stress on the caregivers, and the informed decision-making of the clinicians can be reduced with the help of automated and objective screening tools. Motivated by these challenges, this study attempts to exploit the progress in artificial intelligence (AI) and optimization methods so as to develop a reliable and practical ASD detection framework based on facial image analysis.

1.4. Objectives

The principal goals of the research work are:

- To design a self-operating framework for the early detection of ASD based on facial image analysis of children.
- To adopt a pre-trained ResNet50 model for extracting robust and high-level facial features through transfer learning.
- To apply PSO for selecting the most relevant and discriminative feature subsets, thereby reducing dimensionality and redundancy.
- To implement an SVM classifier for accurate two-class classification, distinguishing autistic from non-autistic subjects.
- To examine the effectiveness of the proposed OPFSVM model using standard performance metrics and benchmark against existing top-performing approaches.

2. Literature Review

Current developments in ML and DL have played a major role in the automated identification and categorization of ASD. Researchers have examined many different types of computational methods, from facial image analysis to modelling behavioural data to hybrid learning frameworks to increase early ASD screening and diagnostic precision.

Atlam et al. [13] proposed a DL-based approach for ASD identification utilizing facial landmark analysis. The research used transfer learning architectures like MobileNetV2 and hybrid VGG-16, and several ML classifiers to identify autistic and non-autistic kids from static images of faces. Using an open-access dataset sourced from Kaggle with 2,940 images, MobileNetV2 gave an accuracy of 92% when classifying the images. The authors highlighted that children with ASD have unique morphological characteristics on their faces, such as the upper facial regions being wider and the inter-ocular spacing also changed, which can be successfully captured with the deep convolutional features. However, the framework did not include explicit feature selection or optimization techniques, which may impact computational efficiency and scalability.

Israr Ahmad et al. 2024 [14] evaluated a number of pre-trained CNN models for ASD detection by using transfer learning. Out of the architectures tested, ResNet50 achieved the best accuracy of 92%, which is higher than the accuracy of the other models, like ResNet34, VGG16, VGG19, MobileNet, and AlexNet. The study proved the power of deeper residual networks in the extraction of discriminative facial features. Nevertheless, the focus of the work was mainly on deep feature extraction and classification without feature redundancy and model optimization strategies.

Alkahtani et al. (2023) [15] explored the use of automated identification of ASD with explainable DL models to increase transparency and interpretability in medical evaluation and decision processes. The research made use of explainable AI methods to visualise areas of the face that contribute to the classification of ASD. Although the methodological contribution focused on interpretability, which is a key element in medical AI, the article was later retracted because of ethical issues surrounding the use of non-curated facial images of minors without confirmed diagnoses or documented consent. This is one of the limitations that restricts the clinical reliability of the results and explains the necessity of ethical data management in ASD research.

Mahmoud M. Abdelwahab et al. [16] compared the performance of some ML classifiers like Random Forest (RF), Logistic Regression (LR), Naive Bayes (NB), Support Vector Machine (SVM), K-Nearest Neighbours (KNN), and Decision Tree (DT) models to predict ASD in different age groups. The study entailed the utilisation of openly accessible non-clinical datasets of different repositories, such as Kaggle and UCI, including data on toddlers, children, adolescents, and adults. While the results showed the potential of ML-based prediction of ASD, the approach was limited to structured tabular data and did not investigate facial image-based deep feature extraction.

Jyotismita Talukdar et al. (2023) [17] investigated the supervised ML algorithms Naïve Bayes, Random Forest, and SVM for ASD diagnosis in toddlers aged between 12 and 36 months, using non-clinical screening datasets. The study was a comparative evaluation of classification models for early screening of ASD. However, the work was restricted to data based on questionnaires and did not include visual or facial features, which may provide more diagnostic clues.

Samar Hazim Hammed et al. (2023) [18] proposed a two-stage ML framework using real-world data with 983 patient records with 45 features. The first stage was the data preparation stage, normalisation, and selection of the features, and the second stage was classifiers such as DT, RF, KNN, NB, AdaBoost, Gradient Boosting, and Neural Networks. The highest accuracy was obtained for the Gradient Boosting model (87%). In spite of good performance, the study relied on structured clinical features and not on image-based representations. Nimmi Vijayan et al. (2025) [19] proposed a DeepDeblur-DOCNN for the ASD detection using noisy and blurred facial images. The framework included image enhancement and then an optimized CNN architecture that was optimized using the Fire Hawk Optimizer. Experiments run on the Children's Facial dataset of ASD from Kaggle showed an accuracy of 96.94% for detection with less model complexity. Although the approach was highly accurate, the multi-stage architecture added complexity to the system and may restrict the generalizability and real-time deployment.

Vijayalaxmi N. Rathod (2025) [14] proposed the use of a Multilayer Perceptron (MLP) based framework for ASD prediction and to classify the severity of ASD in different age groups using non-clinical data sets from Kaggle and UCI. The model that was created involved a dual-stage model that included explainable AI techniques, specifically SHAP, in order to determine the relevance of features, as well as the severity-level classification. While the framework had high levels of accuracy and interpretability, the main features used were behavioural and demographic data rather than facial image-based features.

2.1. Summary of Existing Literature

The reviewed studies show that both facial image analysis based on DL and traditional machine learning techniques have shown high effectiveness in ASD classification and detection. Models that are related to Transfer learning, like MobileNetV2 and ResNet50, have been found to be highly accurate in classification by extracting discriminative facial features, and ML classifiers using behavioral and demographic information have been used to support early screening in different age groups.

Nevertheless, most of the existing approaches are founded on high-dimensional deep features without feature optimization, non-clinical or ethically constrained data, or limited age groups. Also, the architecture of some of the high-performing models is complicated and can influence scalability and applicability in real-time.

2.2. Research Gaps

Despite notable advancements, several research gaps remain evident:

- Limited integration of deep facial feature extraction with intelligent feature selection and optimization techniques**.**
- Overreliance on single classifiers or complex deep architectures**,** increasing computational cost, and overfitting risk.
- Use of non-clinical or ethically unverified datasets reduces reliability and real-world applicability.
- Insufficient evaluation of model performance across diverse age groups and heterogeneous ASD populations**.**
- Lack of emphasis on computational efficiency and scalable frameworks suitable for practical deployment.

These gaps demonstrate the necessity of an optimised hybrid model that will be able to combine deep feature extraction, feature selection, and strong classification to enhance early ASD detection and be efficient, ethical, and generalizable.

3. Research Methodology

This study has created an ASD based on an ML framework with an optimised multi-layer framework, and the entire process occurs in many stages of data collection, image pre-processing, pre-trained feature extraction, selection, and classification.

This segment discusses the comprehensive procedure included in the classification of ASD, utilising the design that was put into place, with Figure 2 defining the process flow. Table 1 represents the list of symbolizations utilized in this article and their summary.

Table 1. Notation and description

Notation	Description
M	moving particles
i^{th}	position particle
T^{th}	Epochs
p_b	particle best
g_b	global best
w	inertia weight
c1 and c2	acceleration constants
r_{1d} and r_{2d}	random method range
$\psi_{\mathcal{S}}$	classification performance
|n|	no. of feature set
|s|	feature set length

3.1. Dataset Gathering

In this ASD classification in the facial images, the dataset attained is the Autism Image Dataset for efficiently classifying ASD. This dataset is freely accessible on the Kaggle site [21]. For this study, the dataset named the "Autism Image Data" is utilized. It contains 3,374 facial images of children, with 2,000 labelled as autistic and 1,374 as non-autistic. This provides a balanced distribution for training and testing models to differentiate between autistic and non-autistic facial features. It remains an initial resource for exploring the role of facial biometrics in ASD detection,

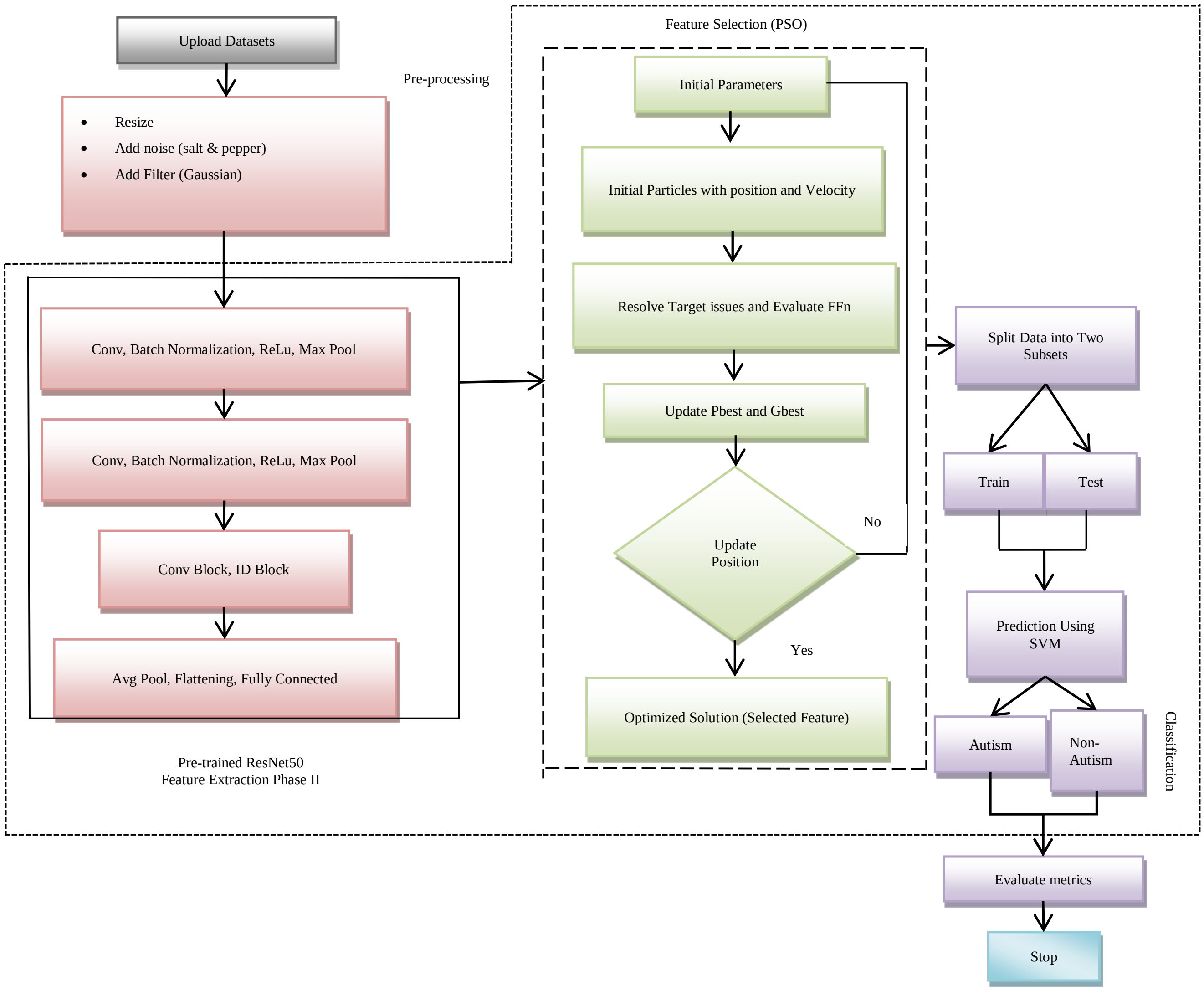


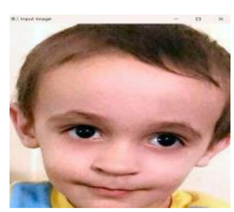
Fig. 2 Proposed architecture of workflow

Although the dataset does not provide some demographic and clinical information, including age, gender, and distribution of ASD severity scores.

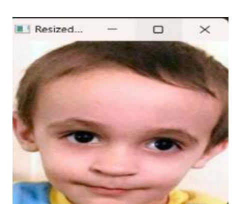
The dataset size is relatively small in comparison to the optimal size of the dataset that is needed to train the DL models, which provides a significant step towards making research in this vital area possible. The 2,294 photos in the data set were divided equally into equal numbers in the autistic and the non-autistic groups, where each group had 1,147 photos, as shown in Figure 1.

3.2. Image Pre-Processing

It is a vital phase to verify the enhanced image clarity and consistency of input data in the ML workflow. Image resizing is the essential pre-processing step in computer vision. It includes managing the image dimensions to a desired size. Normally, ML methods or models train rapidly on small images. The maximum input images need the ML models to acquire further pixels, resulting in a longer training period. Following the resizing procedure, the input facial image data is altered into 224*224, which means that every facial image in the dataset has a continuous size. It constantly improves the training model because ML needs input facial images of a similar size. After the facial images have changed sizes, this gives rise to calculation limitations and delays the framework's capability to acquire designs equally through distinct sections. Figure 3 (i) shows the sample image, and (ii) shows the resized image.



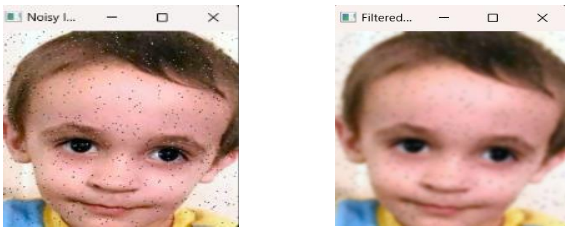
(i)



(ii)

Fig. 3 (i) Input image, and (ii) Resized image.

After the resizing step, it introduces the artificial noise, which is the "Salt and Pepper" distortion or noise. This category of distortion normally degrades the image quality by randomly affecting some pixels to either completely black or completely white.



(i) (ii)

Fig. 4 (i) Noisy image, and (ii) Filter image.

This noise is replicated by considering two probabilities (Prob.): (i) salt_prob and pepper_prob. The noisy image is represented in Figure 4 (i). After that, a Gaussian filter was applied for image processing in this work. This filtration method calculates the smoothness of the facial image using the weighted averaging method, where pixels closer to the center value are closer to the final value, creating a smooth transition. Figure 4 (ii) shows the filter image after the noise reduction.

3.3. Feature Extraction

This section helps with early-stage autism detection; input samples (images) are extracted using pre-trained ResNet50. ResNet50's pre-trained technique manages the hyperparameters and system backgrounds of the powerful ResNet50's complexity, skip connections, computational efficiency, and pre-trained Weights (Wts). The effectiveness makes it a brilliant selection for extracted features in the tasks. Where removing vigorous and classified characteristics from facial images is important, it is completed by designing a ResNet50 method utilizing present variables by image pre-processing the attained database. A convolution is carried out in the initial layer utilizing 64 different kernels, each with a kernel_size of 7*7 and a stride_size of 2. This approach stride_size is 2, and the following step is MaxPooling. Three sizes are available for ensuring convolution:

- 1*1 with 64 kernels
- 3*3 with 64 kernels
- 1*1 with 256 kernels.

Because these layers are performed more than once, this step consists of 9 layers. The extraction procedure then involves 128 kernels of 1*1, 3*3, and 512 kernels with 1*1, and it is finalized in 4 epochs. 18 layers are then created by employing 256 kernels with 1*1, 256 kernels 3*3, and 1024 kernels. The addition of one more step is 512 kernels of 1*1. Then, for a total of 9 levels, there are two more layers with 512 kernels of 3*3 and 2048 kernels of 1*1.

A total of 2048 feature sets are extracted from the dataset as an outcome of the feature extraction procedure. The Particle Swarm Optimization (PSO) method is then used in this study's feature selection procedure, which is thoroughly described in the parts that follow. Figure 5 illustrates the graph for feature extraction. Figure 6 represents the ResNet50 architecture for feature extraction.

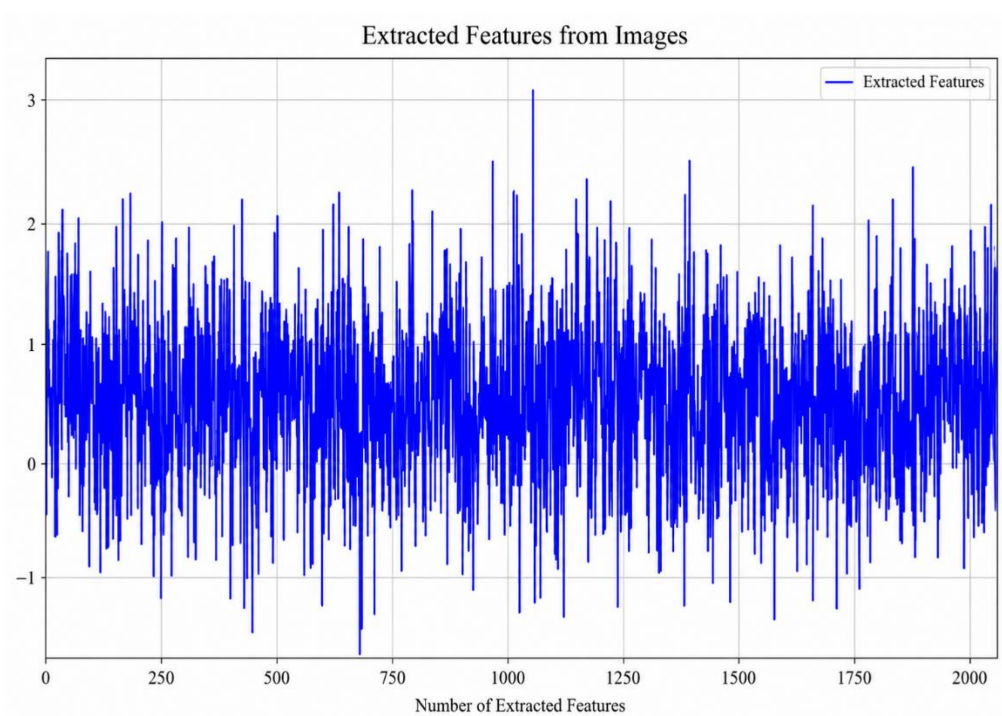


Fig. 5 The representation based on extracted feature values

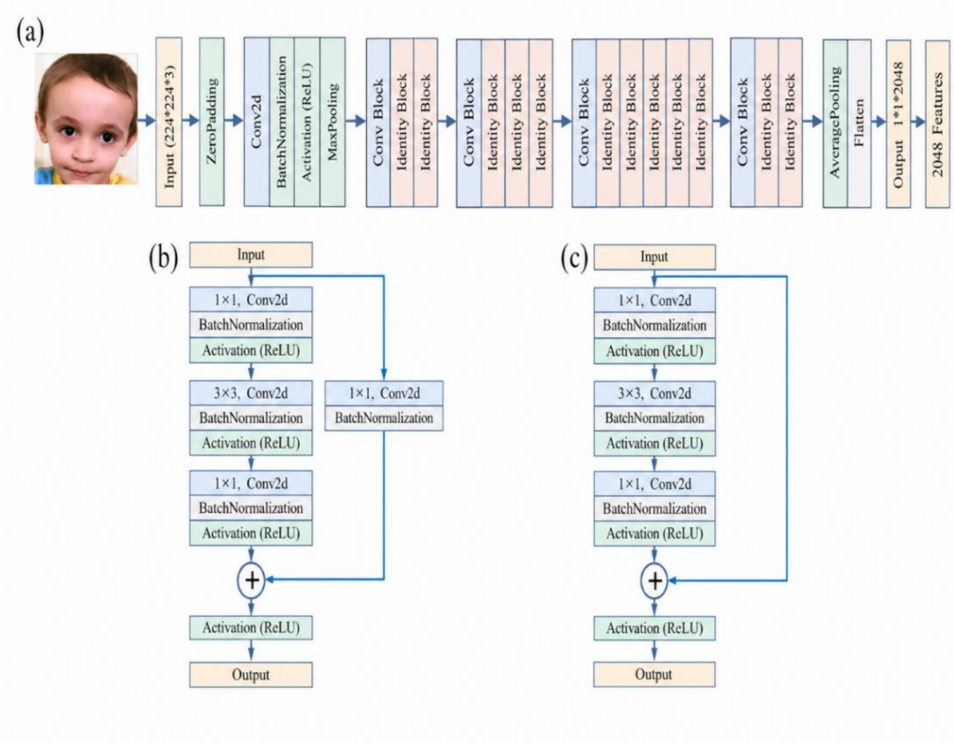


Fig. 6 The architecture of pre-trained feature extraction using RestNet50: (a) 224x224x3 input spectrogram, (b) "Conv Block" module, and (c) Detailed "identity block" module [22].

3.4. Feature Selection

The feature selection process plays an essential role in improving the efficiency of ML methods by identifying the crucial and relevant features while reducing dimensionality. The PSO [23] for feature extraction in the Autism or non-autism facial image dataset suggests a robust method personalized to the difficulties of face imaging. The proposed PSO adjusts to high-dimensional feature sets and reduces computational determinations by accepting database inconsistency.

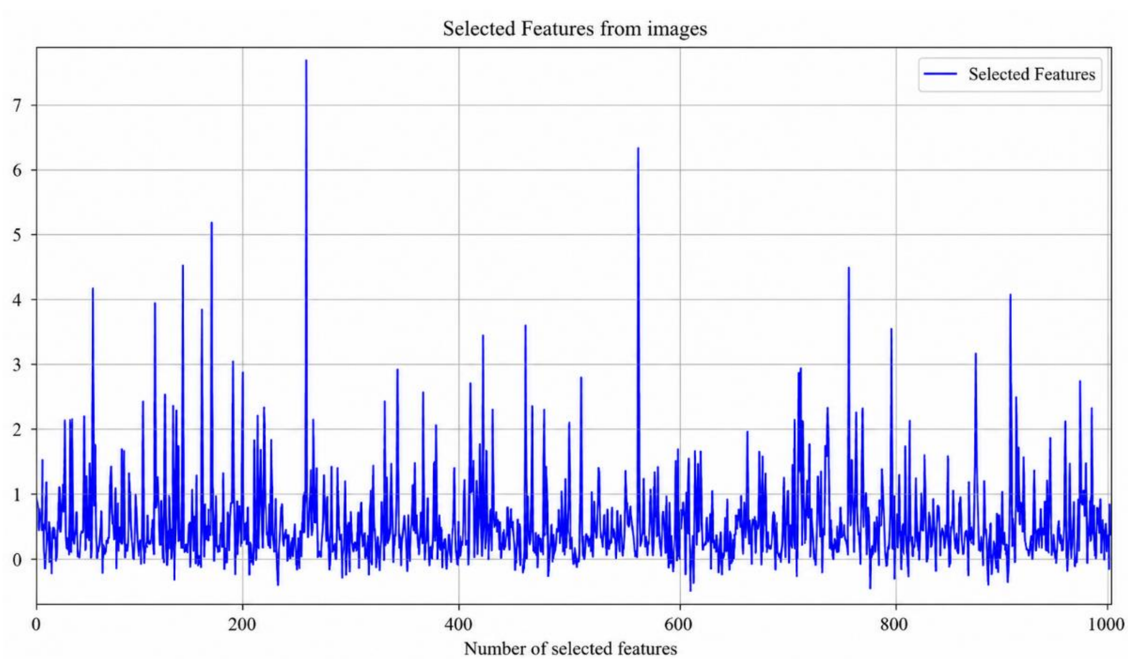


Fig. 7 The representation based on the selected feature sets

It establishes performance in difficult tasks and proposes that its efficiency improves feature selection procedures, confirming the extraction of a feature set suitable for precise and dependable facial image analysis and detection. Figure 7 shows the selected feature set in the line format. Here, the PSO method steps are discussed:

3.4.1. Positional representation

PSO is a set of Mparticles affecting an d-dimensional search space. The i^{th} position particle at T^{th} epochs are defined by $x_i^T = (x_{i1}, x_{i2}, \dots \dots . x_d)$. The best-fit position comes across by a particle (P_b) is signified as $P_i = (p_{i1}, p_{i2}, \dots \dots p_{id})$ and the best-fit position met by the complete swarm (g_n) is signified as $P_g = (p_{g1}, \dots \dots p_{gd})$ All bits define a feature set, and the value "1" denotes the chosen consistent feature set. So, each location is a feature subset.

3.4.2. Velocity Representation

All velocity positions are defined as positive integers, changing between 1 and V_max. It suggests how many features should be modified to be similar to those of the gbest position. Several bits between two particles are based on the variance between their locations. The velocity rate for particle i at epochs T is defined as $V_i^T = (v_{i1}, \dots . v_{id})$.

3.4.3. Update Location Plans

The feature consecutively manages its location toward the global optimization according to Equations (2) and (3);

$$v_{id}\,(T+1) = w * v_{id}\,(T) + c_1 . r_{1d}\,(t). \left[p_{id(T)-}\, x_{id}(T)\right] + c_2 . r_{2d}\,(T). \left[p_{gd(T)-}\, x_{id}(T)\right], \quad (1)$$

$$x_{id}\,(T+1) = x_{id}(T) + V_{id}\,(T+1) \quad (2)$$

Here, w is the inertia wt.; it is an optimistic linear purpose of time-varying and allowing the group epochs. The c1 and c2 define acceleration constants in Equation (1) and define the wt. of the stochastic acceleration relations that pull each particle to p_b and g_b positions. r_{1d} and r_{2d} are dual random methods in the range [0, 1].

3.4.4. Fitness Function (FFn)

It is shown in Equation (3)

$$Fitness = \alpha + \psi s + \beta * \frac{|n| - |s|}{|n|} \quad (3)$$

Where

ψs = Classification performance of the feature sets s,
|n| = no. of feature sets.
|s| = feature set length
$\alpha \in [0,1]$ and β = 1- α.

This mathematical equation shows that the classification presentation and feature set dimension have distinct importance for the feature selection task. It supposes that the organization quality is more crucial than sub-set length, and it selects α= 0.8 and β = 0.2.

The major phases of the implemented feature selection method are defined in Figure 8. The procedure is staged by creating a population of particles with random positions in the search space. The following stage is evaluating each particle. gbest and pbest are evaluated at the end of each epoch, and if the superiority of the answer searched by a particle is greater than its existing pb.

This explanation will be the novel PB for the particle, and the best PB between all particles is chosen as gb. In the subsequent phase, exit principles are analyzed; when an optimized subset has been explored, or the method has been performed a particular no. of times, then the procedure halts, and the finest feature set is met. If none of these circumstances hold, then velocity particles and position are efficient according to Equations (1) and (2), then the procedure epochs are once additional.

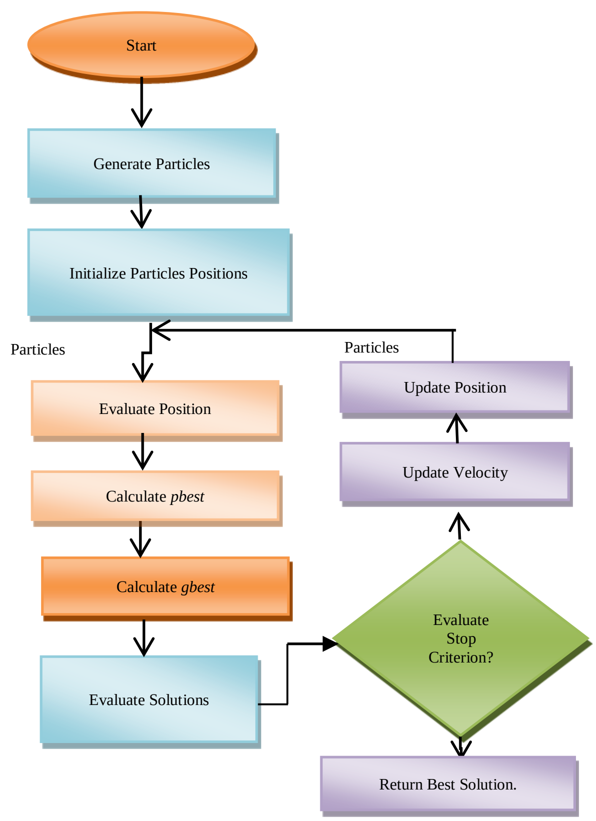


Fig. 8 Flowchart of PSO

3.5. Classification

Once a specific number of features, the notable and dependable feature sets are utilised in the process of the organisation. This is essential in facial imaging, where sophisticated spatial features and structures are important in categorising the images accurately. The capability of the SVM to handle variable input size and the SVM classification tasks attests to the robustness in various imaging modalities. SVM is among the prevailing supervised models that are commonly applied in classification tasks. It is a crucial component because it is efficient in high-dimensional spaces, flexible in the choice of the kernel, and resistant to overfitting. After pre-processing, feature extraction, and selection, SVM was used as the last classification strategy in this study to differentiate between images with and without Autism.

The process works by the outcome of a hyperplane that best splits data points of various classes. The goal of this strategy is to exploit the separation between the closest data points and the hyperplane from each session, which are known as Support Vectors (SVs). This maximization benefits in enhancing the overview capability of the model [24]. Typically, SVM's efficiency is determined by the caliber of characteristics it receives. Therefore, early implementation of feature extraction and selection is necessary to improve its performance. An SVM classifier was used using an RBF kernel. When it comes to non-linear problems of classification, RBF is often used. It enables us to plot a linear decision boundary by mapping the input into a higher-dimensional feature space. Training and testing feature vectors were created by first extracting them using ResNet50 and then fine-tuning them using PSO. Eighty % of the feature vectors are utilized to train the model, and the rest are held for analysis. To optimize the disparity between the two programmes, including non-autistic and autistic, the system is trained to create a hyperplane. To make the process more efficient, cross-validation was utilized to optimize hyperparameters, including kernel-related parameters. In addition, the regularization coefficient and this approach take advantage of the classifier's non-linearity and learned patterns to accomplish top-notch classification efficiency. The following findings verify that the method has the potential to detect vulnerable persons by making alternatives for interventions available at appropriate times, aside from identifying the early onset of Autism.

3.6. Proposed Optimized Pre-trained Feature Selection Support Vector Machine (OPFSVM)

The proposed OPFSVM architecture integrates the advantages of classical ML, meta-heuristic optimization, and transfer learning to provide a highly precise and computationally effective method for detecting Autism in facial photographs. The first step in the OPFSVM workflow is the extraction of high-dimensional feature representations from input photos using ResNet50, a deep residual NN pre-trained on the ImageNet dataset. Only the most relevant and important elements are identified and kept by utilizing the PSO strategy from the extracted collection. This approach reduces computing complexity and enhances classification performance by eliminating superfluous or noisy information. PSO has been hybridised with the Combination-Based Feature Selection (CBFS) to further expand the quality of particular features. After the best features are chosen, the improved dataset is input into an SVM classifier using an RBF kernel. Its operations work effectively with non-linear decision boundaries by mapping the input space to a higher dimension that is advanced enough, and the classes of data are linearly separable. The introduced architecture makes full use of the advantage of each part one by one by using the pre-trained ResNet50 as feature extraction, PSO-CBFS as feature selection, and SVM as final classification. This proposed hybrid structure provides a scalable and flexible system suitable for practical clinical applications in addition to helping in the early and accurate detection of ASD.

3.7. Hyperparameter Tuning, Overfitting Control, and Bias Mitigation

Systematic hyperparameter tuning, overfitting control, and bias mitigation strategies were employed in the development of the proposed OPFSVM framework to guarantee strong performance and generalisation of the proposed framework, as shown in Table 2.

3.8. Model Validation Strategy

To check the performance and stability of the proposed OPFSVM framework, a rigorous validation strategy was used. An 80:20 ratio was applied to separate the dataset into training and testing subsets. The hyperparameters were tuned to cross-validate to ensure that the model attains the same results on multiple folds of the data. Some of the performance metrics that were used to evaluate the model include accuracy, precision, recall, F1-score, sensitivity, and specificity, which provide a comprehensive assessment of the classification capability. The comparison to baseline DL and ML techniques also demonstrated the excellence and strength of the suggested solution.

Table 2. Hyperparameter tuning, overfitting prevention, and bias mitigation strategies used in the proposed OPFSVM model

Component	Parameter / Strategy	Description	Purpose
PSO Feature Selection	Swarm size	Empirically selected to balance search diversity and computational cost	Prevent premature convergence
	Inertia weight (w)	Linearly decreased during iterations	Balance exploration and exploitation
	Acceleration coefficients (c_1, c_2)	Set to maintain equilibrium between individual and social learning	Improve convergence stability

	Maximum iterations	Fixed upper bound on optimization cycles	Ensure termination and efficiency
SVM Classifier	Kernel type	Radial Basis Function (RBF)	Handle non-linear separability
	Regularization parameter (C)	Optimized via cross-validation	Control margin–error trade-off
	Kernel parameter (γ)	Tuned using grid search	Improve decision boundary accuracy
Overfitting Control	Transfer learning	Pre-trained ResNet50 used for feature extraction	Reduce model variance
	Feature dimensionality reduction	PSO removes redundant and irrelevant features	Improve generalization
	Cross-validation	k-fold cross-validation during training	Prevent overfitting
Bias Mitigation	Class balance	Balanced autistic and non-autistic samples	Reduce class bias
	Stratified data split	Maintains class proportions in training/testing	Fair evaluation
	Multi-metric evaluation	Accuracy, precision, recall, F1-score	Avoid misleading performance
Validation Strategy	Train-test split	80:20 ratio	Robust generalization testing

3.9. Comparative Analysis using Different Classification Models

An analysis of comparison was done in this work to assess the extent to which different classification models distinguished ASD from typical controls. The best classifier was identified by comparing the architecture of each model, its strengths, and task fit. The models used for analysis were MobileVNet, ResNet-50, ResNet-34, AlexNet, and a DNN.

3.9.1. MobileNet

MobileNet is a secure and lightweight version of U-Net that is specially designed for resource-constrained and mobile environments. Its architecture exploits depth-wise separable convolutions to have a high performance and low complexity. This technique provides a powerful framework for collecting important features in the selection process for identifying ASD and performs well in segmentation tasks. It is a competitive choice that achieves a balance between speed and accuracy due to its effectiveness and adaptability to different input dimensions [25].

3.9.2. ResNet-50 and ResNet-34

The residual learning framework solves the problem of decreasing gradients and makes the training process significantly better, making it possible to train highly deep networks. ResNet-50 has the ability to process complicated patterns in ASD datasets because it has 50 layers that boost its ability to extract features [26].

On the other hand, ResNet-34 provides an easier layout, which is handy in scenarios where the processing power is limited. The capacity of both models to categorize ASD was evaluated. The 50-layer architecture with the deeper network structure of ResNet-50 resulted in it achieving greater accuracy than both.

3.9.3. AlexNet

It is one of the earliest deep-CNN designs that advanced the field of computer vision. This model was trained on the large ImageNet dataset, including over a million images around 1,000 distinct categories [14]. The model features five convolutional layers along with three fully connected layers. This paradigm works well with comparatively smaller datasets and is less complicated than contemporary systems. Its architecture is very superficial, but it has been largely updated and improved to classify TC and ASD by displaying its ability to extract distinctive traits.

3.9.4. Deep Neural Networks (DNN)

A type of ANN incorporating more than a single hidden layer within the network architecture is the DNN. They perform well in challenging operations such as image recognition due to their capability to learn hierarchical representations of data. These networks are highly flexible because they can perform complex pattern recognition and learning tasks hierarchically owing to their depth [27]. The deeper networks can overcome the vanishing gradient problem by using improved activation functions, including ReLU and the residual connections in ResNet. Recent progress in regularisation techniques, such as dropout and optimization techniques, has allowed DNNs to avoid overfitting. Such developments have produced advanced solutions to a wide range of applications, including voice and image recognition. In this way, DNNs are applied to ML workloads.

4. Simulation Result Analysis

4.1. Implementation Details

Table 3 summarises the implementation environment and experimental setup used in measuring the performance of the proposed OPFSVM model. The model was simulated and implemented in the Python software package, and its performance was assessed in terms of standard evaluation metrics to ensure that the model is reliable and effective. The different techniques used in the performance assessment are provided in Table 4. They make a thorough examination of the categorization abilities of the method and validate the dependability and efficiency of the method for the respective usage.

Table 3. Implementation details of the proposed OPFSVM model

Parameter	Description
Research Objective	Performance analysis and validation of the proposed OPFSVM model
Programming Environment	Python
Development Tool	Graphical User Interface (GUI) package
Operating System	Windows 11 (64-bit)
Processor	Intel Core i7
RAM	32 GB
Execution Mode	Simulation-based execution
Performance Evaluation	Classification performance assessment
Evaluation Metrics	Accuracy, Precision, Recall, Sensitivity, Specificity, F1-score (Equations iv–viii)
Purpose of Evaluation	To examine the classification capability, reliability, and efficiency of the OPFSVM model

Table 4. Performance evaluation metrics

Metric	Mathematical formula	Description
Accuracy	Accuracy=TP+TN/TP+TN+FP+FN	Measures the overall correctness of the classification
Error Rate	Error Rate=FP+FN/TP+TN+FP+FN	Represents the proportion of incorrect predictions
Precision	Precision=TP/TP+FP	Indicates how many predicted positives are actually correct
Recall (Sensitivity)	Recall=TP/TP+FN	Measures the ability to identify +ve samples correctly
F1-Score	F1-Score=2*Precision*Recall/Precision+Recall	Harmonic mean of recall and precision

4.2. Performance Analysis of ASD Facial Image Detection

To assess the suggested OPFSVM model using the effectiveness metrics listed in the earlier equations, this section combines the feature selection and classification procedures. In Table 5, the results calculated to assess the efficiency of the proposed OPFSVM model are displayed.

Table 5. Proposed OPFSVM model: performance analysis

Metrics	Values (%)
Accuracy	97%
Precision	97%
Recall	94%
F1-score	97%
Error rate	3%

The model proved to be extremely efficient in classifying the datasets linked to ASD, as evidenced by its accuracy score of 0.97. Precision demonstrated its reliability in finding relevant examples and obtained a score of 0.97. Recall was 0.94, while the F1-score of 0.97 showed that precision and recall were balanced.

The low error rate of 0.03 in this inquiry finally validated the accuracy and robustness of the suggested methodology. A graphic depiction of the entire efficiency is shown in Figure 9. Figure 10 represents the performance of the proposed Optimised Pre-Trained Feature Selection With Support Vector Machine (OPFSVM) model in autism detection as a confusion matrix. The table indicates that the model was very accurate, with a high score of 97 %, identifying 470 autistic and 485 non-autistic cases. Although the model sometimes confused non-autistic children with autistic ones (15 false positives) and autistic children with non-autistic ones (30 false negatives), the error rate is low at only 3 %.

The model has a 96.9% precision, which means that the majority of the identified autistic cases by the model are accurate, whereas the recall of 94% means that the model is good at identifying most of the real cases of Autism. The balance between precision and recall is also indicated by the F1-score of 95.4%. These findings show the strength of the OPFSVM model, which can be used as an effective instrument for early ASD detection through the analysis of facial images.

Table 6 presents the predicted classification outcomes by showing the distribution of instances between the two categories: "Autism" and "Non autism." The model classified 136 instances as "Autism" and 118 instances as "Non-autism".

This distribution provides an overview of the classification results of the model and highlights its ability to distinguish between the two classes based on the provided dataset. Visual representation is presented in Figure 11.

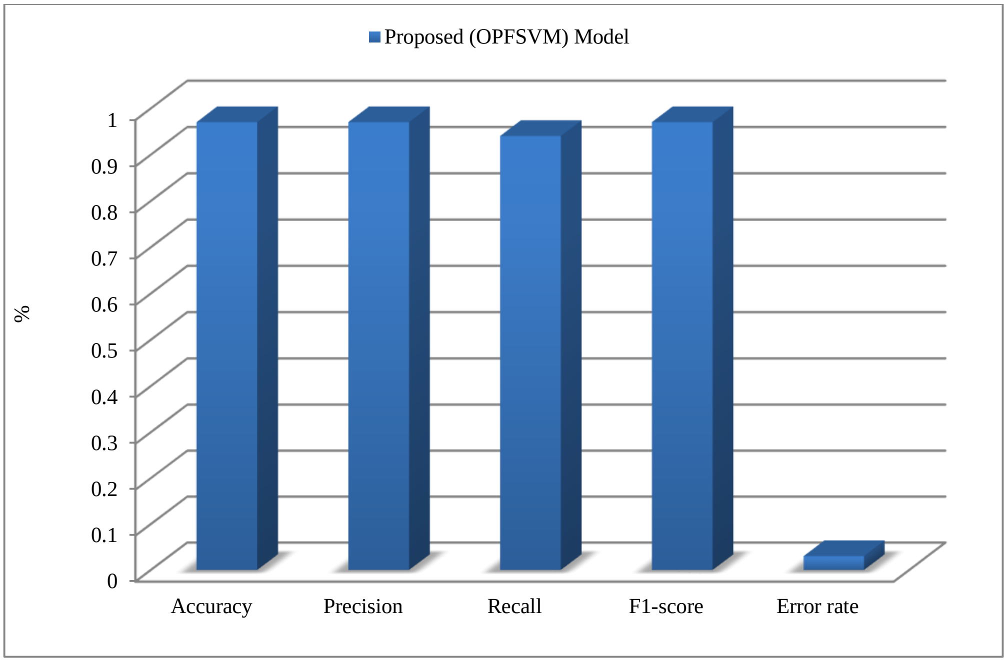


Fig. 9 Visual representation of the different presentations of the proposed OPFSVM model

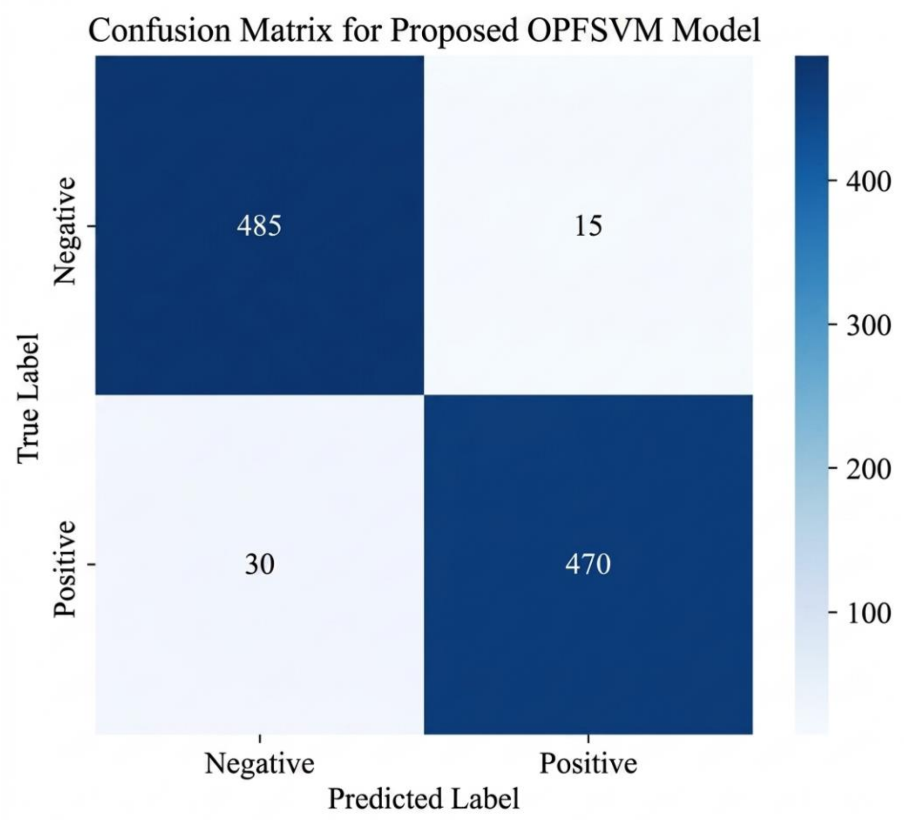


Fig. 10 Confusion matrix for proposed model

Table 6. Predicted class distribution

Class	No. of Values
Autism	136
Non-autism	118

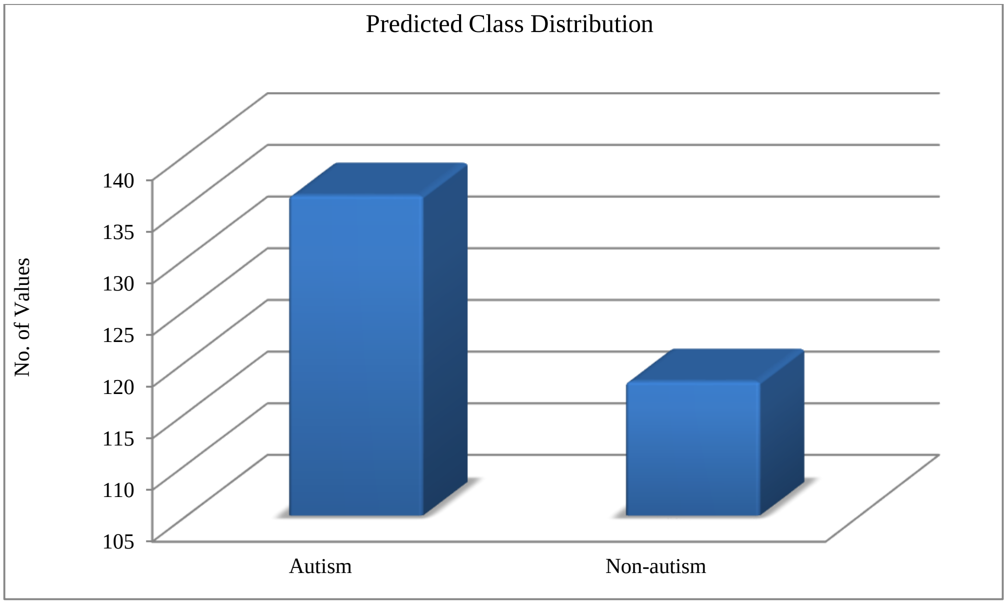


Fig. 11 Visual representation of the predicted class distribution

Table 7 provides a proportional analysis that highlights the performance of ResNet50, DNN, and the planned OPFSVM model.

The planned OPFSVM model demonstrated superior performance, outperforming both models. Figure 12 presents a visual representation of comparative analysis.

Table 7. Comparative analysis of the different performances of ResNet50, DNN, and the proposed OPFSVM model

Performance Metrics	Models		
	ResNet50	DNN	Proposed OPFSVM
Accuracy	80	77	97
Precision	80	77	97
Recall	72	77	94
F1-score	77	77	97
Error Rate	20	23	03

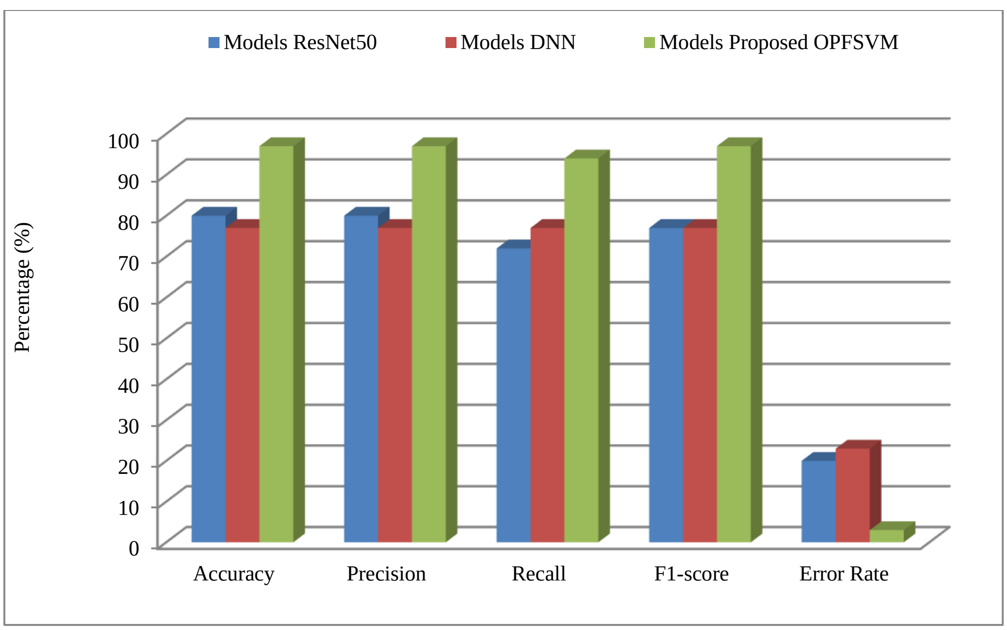


Fig. 12 Visual representation of comparative analysis among ResNet50, DNN, and the proposed OPFSVM model

A detailed evaluation was conducted for the presentation of numerous DL methods based on their accuracy and error rate, as accessible in Table 8. Models such as MobileNet, ResNet50, ResNet34, Vgg19, AlexNet, and DNN are included, along with a proposed model result with PSO (OPFSVM). Among all the models listed, the proposed OPFSVM model stands out with impressive results and makes it the most accurate model for detecting ASD from images in early childhood.

Table 8. Accuracy and error rate-based comparison of various methods

Models	Accuracy	Error Rate
MobileNet	79	21
ResNet50	80	20
ResNet34	76	24
Vgg19	81	19
AlexNet	77	23
DNN	77	23
Proposed OPFSVM	97	03

A visual representation of this comparison is illustrated in Figure 13. As shown in Table 9, the ResNet50 model exhibited higher effectiveness relative to alternative models.

However, the proposed OPFSVM model surpassed ResNet50, making it a more effective and reliable option for ASD detection.

Phase 1, Phase 2, and Phase 3 represent three successive training phases: initial transfer learning (only the last layer), partial fine-tuning (the last two layers), and full fine-tuning (All layers) of the pre-trained CNN models [14].

The reported results for the proposed OPFSVM represent the average performance obtained over multiple experimental runs. Since OPFSVM does not follow phased CNN fine-tuning, phase-wise results are not applicable. Therefore, only the averaged final accuracy and error rate are reported for comparison.

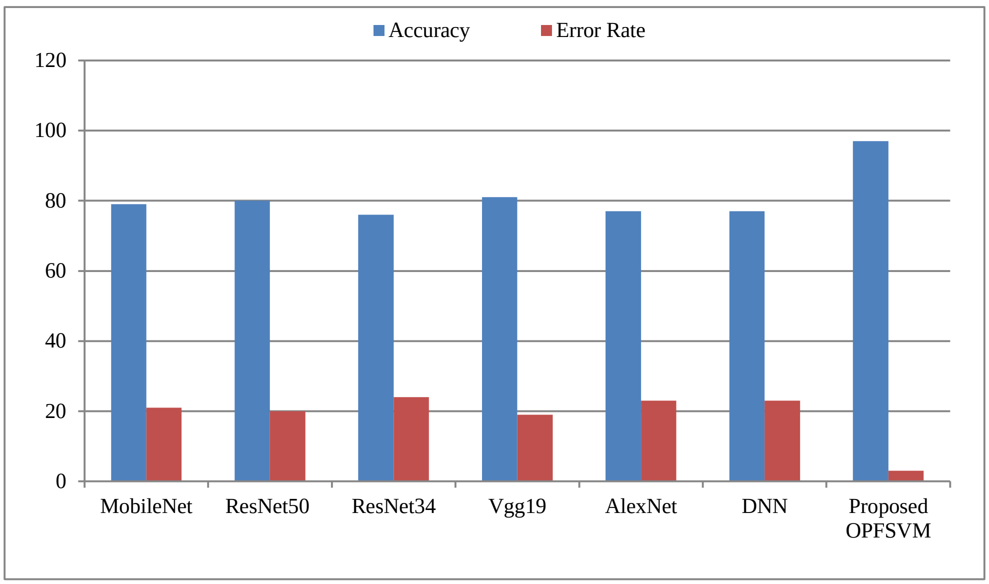


Fig. 13 Comparative analysis of various methods based on accuracy and error rate

Table 9. Comparative analysis of various models based on performance metrics [14]

Model/Parameters	Phase I	Error	Phase II	Error	Phase III	Error
MobileNet [14]	79	21	82	18	85	15
ResNet50 (124*124) [14]	79	2	82	18	87	13
ResNet34 (124*124) [14]	76	24	83	17	84	16
ResNet34 (248*248) [14]	81	19	83	17	87	13
ResNet50 (248*248) [14]	80	20	85	15	92	8
VGG19 [14]	81	19	85	15	87	13
AlexNet [14]	77	23	75	25	75	25
Proposed OPFSVM	NA	NA	NA	NA	97	3

4.3. Ablation Study

An ablation experiment was done to assess the performance of the Optimised Pre-trained Feature Selection with Support Vector Machine (OPFSVM) model, with and without Particle Swarm Optimization (PSO). The Proposed OPFSVM model, which involves feature extraction by the pre-trained ResNet50 model, and optimization of the feature set by PSO, followed by classification with a Support Vector Machine (SVM), gave 97% accuracy and a low error rate of 3%. This finding highlights the fact that the model can distinguish well between autistic and non-autistic cases with a minimum error. Conversely, the performance declined significantly when the PSO optimization was eliminated in the model. The PSO optimization was not done in the model, which only had 78 % accuracy with a higher error rate of 17%. This significant drop in performance emphasizes the importance of PSO in enhancing the feature selection process by eliminating redundancy and keeping the most useful features. The PSO optimization was used to remove the non-relevant features and improve the classification process, which directly led to the high accuracy and reduced error rate of the Proposed OPFSVM model.

Table 10. Ablation study analysis

Model Variant	Accuracy (%)	Error Rate (%)
Proposed OPFSVM (With PSO)	97%	3%
Model Without PSO Optimization	78%	17%

The results are highlighted in Table 10, showing the significance of using a combination of pre-trained feature extraction and optimized feature selection in order to have high accuracy in detecting Autism. The lack of PSO optimization in the alternative model proves that there is a significant performance difference, which proves that the proposed approach is effective in enhancing the overall detection capabilities.

4.4. Discussion

A new model, named OPFSVM, is proposed in this research. To calculate the proposed OPFSVM model's effectiveness, assessment parameters comprising precision, F1-score, accuracy, and recall were utilized. The findings show that various models currently in use for identifying ASD in facial photos are not as effective as the suggested OPFSVM model.

The suggested model showed great efficiency by attaining a 97% accuracy rate. Both the precision rate and the F1 score were superb at 97%. The 3% minor error rate of the method and 94% recall score further established its flexibility and indicated that it was able to detect all the relevant features. The suggested model was compared with some current models like VGG19, ResNet50, MobileNet, AlexNet, DNN, and ResNet34. The proposed OPFSVM model demonstrates excellent performance compared to the current model. In contrast to the rest of the models, the new OPFSVM model had significantly improved accuracy and error rates. Showing a 17% difference in accuracy compared to the existing ResNet50 model, it proved to be a competent method for the detection of ASD. In total, the outcomes reveal that the newly created OPFSVM model is the most accurate and precise method of diagnosing ASD in children. It outperforms the current well-established DL models, making it a valuable leap in the community and possibly with the potential to apply to ASD detection.

4.5. Explainability and Clinical Integration

The explainability of artificial intelligence-based systems is a vital condition of the implementation of these systems in the medical field, especially in the screening of neurodevelopmental disorders, where the clinical decision has a long-term effect. Before implementing AI tools in their daily practise, clinicians need transparent and understandable models to comprehend the results of prediction, confirm the reliability of the system, and gain trust in the system. In contrast to black-box deep learning models, interpretable or semi-interpretable models increase responsibility and clinical trust. Explainability in the proposed OPFSVM framework is supported partially by its hybrid architecture. A pre-trained ResNet50 model can be used to extract meaningful high-level facial representations, and a based feature selection mechanism can further minimise feature redundancy by keeping only the most discriminative features. The advantage of this dimensionality reduction is that it enhances interpretability by making the classification decision based on a reduced set of optimised features in the face.

The Support Vector Machine (SVM) classifier is also relatively interpretable in its decision boundary, with the predictions being dependent on a relatively small number of support vectors instead of millions of trainable parameters, which is also more appropriate in a clinical setting compared to fully complete pipeline deep learning architectures [27]. Nevertheless, the existing application does not clearly visualise the facial areas that play the most crucial role in the classification of ASD. Past research has shown that explainable AI (XAI) methods, including Grad-CAM, SHAP, and LIME, can be useful to identify salient facial landmarks and areas of the face that are used to make a decision, which enhances transparency and clinical trust [13, 20]. It would be possible to include such visualisation methods in future work and enable clinicians to check whether the model focus corresponds to the morphological features that are known to be related to ASD. Clinically speaking, the proposed OPFSVM model is formed as a decision-supporting system and not a separate diagnostic tool. The facial image analysis is non-invasive and relatively low in terms of computational complexity, and therefore, the system can be applied in screening during the first encounter with patients in paediatric clinics, community health centres, or telemedicine platforms.

The ease of use is also facilitated by the given Graphical User Interface (GUI) because healthcare providers who lack advanced technical skills can use the system efficiently. In real-life scenarios, the model may be useful in helping clinicians to detect high-risk cases that need thorough behavioural and developmental assessment to minimise diagnostic delays and facilitate early intervention strategies [24].

5. Conclusion

The suggested model is very efficient and reliable for the rapid identification of facial images, which is based on ASD. The model is better than other traditional DL models, such as Vgg19, ResNet50, and MobileNet, because of the robust feature selection and perceptive classification strategies. The OPFSVM model shows excellent performance by achieving 97% accuracy, an F1 score of 97%, and a small error rate of 3%. It has the ability to identify faint, typically difficult-to-detect ASD-associated features. The result shows the usability of the method in diagnosing ASD in young children by providing early detection and intervention to those affected. In addition, the incorporation of a Graphical User Interface (GUI) increases the validity and usability of the model as well as the ability of users who do not possess technical expertise in clinical and research environments to use the system. Comparative analyses prove the efficiency of the suggested model compared to other available methods in the area of ASD detection from face photos, with very impressive results. Future studies should enhance the suggested framework by addressing the problem of better feature extraction and accuracy with the help of transfer learning and attention mechanisms. The model will be tested on large and diverse data sets to make it scalable and generalizable. Expanding acceptability in the early diagnosis of ASD also requires the creation of cross-platform applications and real-time applications in the clinical setting.

Conflicts of Interest

The authors report that there are no conflicts of interest.

Author Contributions

Author 1 (Robin Khurana): Topic analysis, problem formulation design, objective, and methodology of the research work designed under supervision, implementation done, review, and research article writing, editing; Author 2 (Satyaveer Singh): supervision, project administration.

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