Emotion-based Autism Spectrum Disorder Detection by Leveraging Transfer Learning and Machine Learning Algorithms

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***Abstract*—Autism Spectrum Disorder (ASD) presents as a neurodevelopmental condition impacting social interaction, communication, and behavior, underscoring the imperative of early detection and intervention to enhance outcomes. This paper introduces a novel approach to ASD detection utilizing facial features extracted from the Autistic Children Facial Dataset. Leveraging transfer learning models, including VGG16, ResNet, and Inception, high-level features are extracted from facial images. Additionally, fine-grained details are captured through the utilization of handcrafted image features such as Histogram of Oriented Gradients, Local Binary Patterns, Scale-Invariant Feature Transform, PHASH descriptors. Integration of these features yields three distinct feature vectors, combining image features with VGG16, ResNet, and Inception features. Subsequently, multiple machine learning classifiers, including Random Forest, KNN, Decision Tree, SVM, and Logistic Regression, are employed for ASD classification. Through rigorous experimentation and evaluation, the performance of these classifiers across three datasets is compared to identify the optimal approach for ASD detection. By evaluating multiple classifiers and feature combinations, this work offers insights into the most effective approaches for ASD detection.**

Keywords—Autism Spectrum Disorder; transfer learning; image features; VGG; ResNet; Inception

I. Introduction

According to the Diagnostic and Statistical Manual of Mental Disorders, Autism Spectrum Disorder (ASD), a neuro-developmental disorder, is defined by reduced sharing of emotions, interests, deficits in reciprocity of social and emotional aspects and a failure to engage in normal conversations. There is also a deficit in nonverbal communicative behaviour that one uses for social interactions. People identified with ASD also fail to develop, maintain and understand relationships that range from finding it difficult to adapt their behaviour according to the social contexts to difficulty in making friends or lacking interesting in peers or engaging in imaginative play [1].

Detection and diagnosis of ASD is indeed very challenging for medical professionals as well as parents as the diagnosis depends predominantly on the aberrations in the functioning of the brain that may not surface in the very early stages of the disorder. Facial expressions and emotional expressions can help in early detection and diagnosis of ASD. This can be accomplished as the autistic children show distinctive patterns. Machine learning, deep learning, artificial intelligence, and affective computing have all helped in detecting the disorder early on and ameliorate the quality of life of these children [2]. This technological advancement has also become a blessing to the parents who are clueless about managing the condition.

Early detection and diagnosis facilitate early intervention which can in turn result in good developmental outcomes and bring about better adaptive skills in the child. It can facilitate the implementation of specialised interventions that cater to specific needs of the autistic child. They would target language development, behavioural challenges and social communication [3].

However, recent advancements in ML DL and data analysis offer promising avenues for improving ASD diagnosis.This paper introduces an innovative approach to ASD detection using facial features extracted from the Autistic Children Facial Dataset. Leveraging transfer learning models such as VGG16, ResNet, and Inception, the high-level features are extracted from facial images to capture essential characteristics indicative of ASD. Moreover, the authors incorporate handcrafted image features like HOG, LBP, ORB, PHASH, and SIFT descriptors to capture intricate details crucial for accurate classification. By integrating these features, three distinct feature vectors are constructed, each combining image features with VGG16, ResNet, and Inception representations. Subsequently, authors employ a suite of machine learning classifiers, including Random Forest, KNN, Decision Tree, SVM, and Logistic Regression, to classify ASD based on the extracted features. Through comprehensive experimentation and evaluation across all three datasets, authors aim to determine the most effective approach for ASD detection. This research endeavor contributes to advancing the development of precise and dependable tools for early ASD detection, facilitating prompt intervention and support for individuals affected by the disorder.

II. Background

In study [4], toddler ASD screening datasets were pooled. A dataset balance was achieved using SMOTE, followed by feature selection. First, an ensemble of random forest and

XGBoost classifiers were used to identify ASD with good accuracy. The research examined ASD children's physical, linguistic, and behavioral performance to determine the best teaching approaches in the second phase. Based on machine learning, this work tailored ASD instruction to individual requirements. In study [5], a scan path-based ASD diagnosis method is proposed highlighting individual differences in attention and spatial distribution. LSTM networks outperformed traditional methods. In study [6], autistic children using deep CNN transfer learning methods is identifed for facial landmark detection. Optimizer settings and hyperparameters were refined empirically to improve CNN model prediction accuracy. Different machine learning techniques were used using MobileNetV2 and hybrid VGG19 transfer learning approaches. MobileNetV2 outperformed other systems on a Kaggle dataset with 92% accuracy. The revised model may help doctors validate kid ASD screening accuracy. Two-phase transfer learning and multi-classifier integration were used in study [7]. Two-phase transfer learning and multi-classifier integration improved classification performance in MobileNetV2 and MobileNetV3-Large, suited for mobile phones. Final categorization results based on participating models' outputs were calculated using a new technique. The composite classifier outperformed separate classifiers in two-phase transfer learning experiments on MobileNetV2 and MobileNetV3-Large. Integrated classifier accuracy was 90.5% and AUC 96%, 3.5% higher than earlier investigations.

In study [8], a triadic VR job interview simulation is used to promote solo gaze behavior and head orientation exercise. Machine learning examined interviewer head orientations with little angular error. Autistic people looked less at interviewers than non-autistic subjects. In study [9], current findings on ML-based ASD screening in newborns and young children were consolidated. It showed the rising frequency of ASD and the promise of machine learning in diagnosis and treatment. Multiple ML approaches were used to educate computers to detect data patterns. Through academic literature searches, the article examined ASD prevalence in the general population. Face pictures were used to predict ASD in study [10].

Through face analysis, authors were able to distinguish children with Autism Spectrum Disorder from normally developing youngsters. For model assessment, the Autism Image data sets included 2530 training and 300 test face pictures. The Efficient Net convolutional neural network built this model with 88% accuracy. The authors in [11] applied hybrid ML models for ASD detection and reported reasonable results. The research in [12] used a UCI repository dataset of pediatric ASD cases to identify them using machine learning and deep learning. The classification challenge used kKNN, SVM, and CNN. CNN outperformed SVM and k-NN with exceptional accuracy. In study [13], the proposed approach detected ASD with 84.79% accuracy using the ABIDE dataset of fMRI data for autistic spectrum disorder. This early and cost-effective detection technology shows potential over symptom-based diagnosis. The proposed strategy in study [14] had potential in aiding early ASD diagnosis using facial cues and ML. It investigated DL algorithms like VGG16 and VGG19, followed by various ML methods such as logistic regression, SVM, naive Bayes, and ANN.

A ML-based strategy to detect ASD in children using behavioral patterns was presented in study [15]. Out of 12 machine learning techniques, Support Vector Machine and Artificial Neural Network have 91% and 96% prediction accuracy. This method might help diagnose ASD early for support and treatment. Several ML-based CADS for ASD diagnoses employing MRI modalities were examined in [16]. Little was done to construct automated ASD diagnosis models using DL methods. DL studies were summarized in the Supplementary Appendix. The problems of automated ASD diagnosis utilizing MRI and AI were detailed. The categorization method in study [17] included Autism-Spectrum Quotient (AQ) Test questions and topic data attributes. SVM was used, however a multi-kernel SVM approach was suggested for difficult non-linear data to boost accuracy. Experimental findings indicated strong autism prediction accuracy and precision for the ASD class. ASD diagnosis using ML was examined in study [18]. Train and test machine learning algorithms using a huge dataset of behavioral and demographic data from autistic and non-autistic people These algorithms were more accurate than existing methods at identifying autism, suggesting that machine learning may be used to diagnose ASD early and accurately. In study [19], ML and image processing were used to help parents, therapists, and Autistic Rehabilitation Centers track progress. CNN, Haar Cascade object detection Algorithm, and TensorFlow classified emotions and picked up faces from autistic youngsters. The study relied on Helping Hands Rehabilitation Center.

DL-based ASD detection was employed in [20] using a hybrid vision transformer and CNN architecture. It has competitive accuracy in differentiating ASD from normally developing youngsters, indicating it might be used in clinical settings for early ASD identification.[21] used boosting algorithms with autistic and normal face samples. Gradient Boosting was most accurate, followed by LightGBM and Adaboost. This shows that boosting algorithms detect autistic and normal faces well. NLP and AI algorithms including decision trees, XGB, KNN, and BERT were used to identify ASD [22]. It categorized Twitter tweets by ASD presence. Over 84% accuracy in recognizing texts from prospective ASD users highlighted the potential of DL models to improve ASD diagnosis. SVM approaches were used to automate ASD diagnosis in children using facial visual patterns in [23]. It tested several SVM kernels using Gray-Level Co-occurrence Matrix feature extraction. The green channel improved system performance by 3.51% and the RBF kernel performed best with a score of 0.73.

In research [24], ML was used to predict ADHD in ASD youngsters using handwriting patterns. Samples were taken from healthy and ADHD Japanese youngsters. Statistical characteristics were retrieved and examined to find the optimum combinations. In research [25], persons with or without autism spectrum disorder are classified using a Kaggle-trained Improved Convolutional Neural Network (I-CNN). High classification accuracy was achieved utilizing feature-based algorithms and optimization to anticipate emotions. In study [26], proposed an optimal deep learning model for emotion analysis to predict ASD and NoASD in 1–10-year-olds. Face landmarks and CNNs were used for categorization and emotion detection, obtaining good accuracy across datasets. The study in [27] used a dataset that was made accessible to the public on the Kaggle platform, dividing training and testing into a 70:30 ratio. In the end, the neural network-based model that was constructed had a 91% accuracy rate and a loss value of 0.53. In study [28], Kaggle and UCI Machine Learning Repository ASD datasets were investigated using feature transformation and strongly co-linear feature elimination. Logistic regression outperformed other classifiers in autism trait detection.

In this paper, authors proposed a methodology to improve accuracy of ASD detection using Machine Learning algorithms by leveraging transfer learning techniques and image features.

III. Method

The proposed methodology for ASD detection in children is shown in Fig. 1. The proposed methodology for detecting Autism Spectrum Disorder (ASD) involves a multi-stage process integrating advanced machine learning techniques with facial feature extraction from the Autistic Children Facial Dataset. Initially, transfer learning models, including VGG16, ResNet, and Inception, are utilized to extract high-level features from facial images. These pre-trained models, which have been trained on large-scale image datasets, possess the capability to capture complex patterns and representations in facial data, enabling effective feature extraction.In addition to transfer learning models, handcrafted image features such as Histogram of Oriented Gradients (HOG), Local Binary Patterns (LBP), Oriented FAST and Rotated BRIEF (ORB), Perceptual Hash (PHASH), and Scale-Invariant Feature Transform (SIFT) descriptors are incorporated. These handcrafted features offer complementary information to the deep learning-based features, capturing fine-grained details and nuances in facial images that may not be fully captured by transfer learning models alone.

Subsequently, three distinct feature vectors are formed by integrating the extracted image features (HOG, LBP, ORB, PHASH, and SIFT) with the features obtained from the three transfer learning models (VGG16, ResNet, and Inception). This integration process results in comprehensive feature representations that combine both high-level semantic information and low-level texture details, enhancing the discriminative power of the feature vectors for ASD detection. Following feature extraction and integration, a range of machine learning classifiers is applied to classify ASD based on the constructed feature vectors. The classifiers employed include Random Forest, K-Nearest Neighbors (KNN), Decision Tree, Support Vector Machine (SVM), and Logistic Regression. These classifiers are trained on the feature vectors and evaluated using rigorous experimentation and evaluation methodologies to assess their performance in ASD detection.

To facilitate a comprehensive comparative analysis, the performance of the machine learning classifiers on all three datasets derived from the integrated feature vectors is evaluated. By comparing the classification accuracies and other performance metrics across different classifiers and datasets, the aim is to identify the most effective approach for ASD detection. Through this research endeavor, the goal is to contribute to the development of accurate and reliable tools for early ASD detection, thereby enabling timely intervention and support for affected individuals.

A. Autistic Children Facial Dataset Collection

Autistic children facial dataset is collected form Kaggle [29]. The dataset comprises 2936 images, evenly divided between autistic and non-autistic children, with 1468 samples in each category. All the images are color images. The dataset comprises only facial images of autistic and non-autistic children.

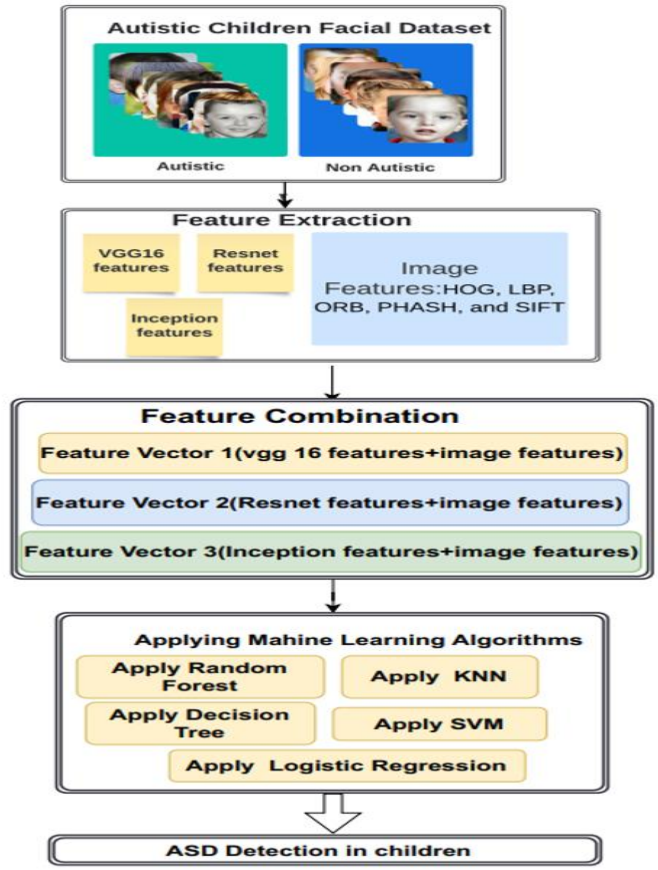

Fig. 1. Proposed model for ASD detection.

B. Feature Extraction

Feature extraction is a crucial step in many machine learning and computer vision tasks, including the detection of Autism Spectrum Disorder (ASD) in children. It involves transforming raw data, such as images, into a more compact and representative form that can be easily utilized by machine learning algorithms for classification or regression tasks. In the context of ASD detection, feature extraction from facial images plays a pivotal role in capturing relevant information that discriminates between individuals with ASD and typically developing individuals. The proposed methodology integrates both deep learning-based approaches and traditional handcrafted feature descriptors to extract comprehensive feature representations.

1) Deep learning-based feature extraction: Transfer learning models such as VGG16, ResNet, and Inception are employed to extract high-level features from facial images. These models are pre-trained on large-scale image datasets, allowing them to capture complex patterns and representations effectively. By utilizing pre-trained models, the methodology leverages the learned knowledge from diverse image datasets, enhancing the capability to extract relevant features from facial images. Deep learning-based features are capable of capturing semantic information and abstract representations in facial data, which are valuable for discriminating between individuals with ASD and neurotypical individuals.

2) Handcrafted feature extraction: In addition to deep learning-based features, traditional handcrafted image descriptors are incorporated to capture fine-grained details and nuances in facial images. Histogram of Oriented Gradients (HOG), Local Binary Patterns (LBP), Oriented FAST and Rotated BRIEF (ORB), Perceptual Hash (PHASH), and Scale-Invariant Feature Transform (SIFT) descriptors are among the handcrafted features utilized. These descriptors focus on capturing texture information, local patterns, and key points of interest in facial images. Handcrafted features offer complementary information to deep learning-based features, enhancing the discriminative power of the extracted feature vectors for ASD detection.

HOG computes gradients' magnitudes and orientations in localized portions of an image and generates histograms of these orientations, capturing local texture information. In the context of ASD detection, HOG can effectively capture subtle variations in facial textures, aiding in discriminating between individuals with ASD and typically developing individuals based on the unique patterns present in their facial features. LBP encodes the local texture patterns of an image by comparing each pixel with its neighboring pixels, resulting in a binary pattern for each pixel. These binary patterns are then histogrammed to represent the texture information of the image. In ASD detection, LBP can capture textural irregularities and subtle facial expressions, providing valuable information for distinguishing between individuals with ASD and neurotypical individuals. ORB is a feature descriptor that combines the FAST keypoint detector with the BRIEF descriptor. It detects keypoints in an image and computes binary feature descriptors around these keypoints, which are invariant to rotation and scale changes. In the context of ASD detection, ORB can extract distinctive local features from facial images, enabling robust matching and discrimination between different facial expressions and characteristics associated with ASD.PHASH generates a compact fingerprint, or hash, for an image based on its perceptual content. It quantifies the visual similarity between images by measuring the similarity of their hash values. In ASD detection, PHASH can help identify recurring visual patterns or features in facial images associated with ASD, aiding in the classification and discrimination of affected individuals from neurotypical individuals. SIFT detects and describes local features in an image, which are invariant to scale, rotation, and affine transformations. It identifies keypoints based on their local intensity gradients and computes descriptors around these keypoints to represent their appearance. In the context of ASD detection, SIFT can extract robust and distinctive features from facial images, facilitating accurate matching and classification of individuals based on their unique facial characteristics and expressions.

C. Integration of Features

The extracted features from both deep learning-based models and handcrafted descriptors are integrated to form comprehensive feature representations. The image features are integrated with three transfer learning features separately to form three feature vectors. This integration process combines high-level semantic information captured by transfer learning models with low-level texture details captured by handcrafted descriptors. By integrating diverse feature sources, the methodology aims to create more discriminative feature vectors that effectively differentiate between individuals with ASD and typically developing individuals.

D. ML Classifiers

The proposed methodology utilizes several ML algorithms including Random Forest, KNN, Decision Tree, SVM, and Logistic Regression after merging features extracted from facial images. Random Forest, an ensemble method, constructs multiple decision trees with random subsets of data and features, offering robustness against overfitting. KNN classifies instances based on the majority class among their nearest neighbors, providing a simple yet effective approach. Decision Tree recursively partitions the feature space into regions, offering interpretability but prone to overfitting. SVM constructs a hyperplane to separate instances, effective for high-dimensional data and nonlinear relationships. Logistic Regression models the probability of binary outcomes, offering simplicity and interpretability. These algorithms collectively aim to classify Autism Spectrum Disorder (ASD) based on the comprehensive feature vectors, contributing to the development of accurate tools for early detection and intervention in affected individuals.

IV. Results and Discussion

A. Extraction of VGG16 Features

The vgg16 feature extraction process begins with importing libraries for image processing, data manipulation, and deep learning. The directory containing the image dataset is specified, with subdirectories representing different classes like "autistic" and "non_autistic". The pre-trained VGG16 model is loaded, focusing solely on feature extraction by excluding fully connected layers. Features are extracted from individual images using predefined methods. Image features are then aggregated into arrays using a specified function. This process is repeated for both the "autistic" and "non_autistic" image directories. Pandas DataFrames are created to organize the features, with separate DataFrames for each class. A label column is added to denote the class label ("autistic" or "non_autistic"). These DataFrames are merged, combining both features and labels. Finally, the merged DataFrame is saved to a CSV file as vgg16_features.csv, completing the extraction process. The number of vgg features extracted are 3000.

B. Extraction of ResNet Features

The ResNet feature extraction process starts by loading the pre-trained ResNet50 model, excluding fully connected layers for feature extraction. Features are extracted from individual images using a defined function. This function preprocesses each image and extracts features using ResNet50. Another function iterates through image directories, extracting features for each image. Features are organized into separate DataFrames for autistic and non-autistic classes, with labels added. These DataFrames are merged, combining features and labels, and saved to a CSV file. This method streamlines the extraction and organization of ResNet features for further analysis or model training. The number of ResNet features extracted are 3000.

C. Extraction of Inception Features

The inception feature extraction process starts by loading the pre-trained InceptionV3 model, excluding fully connected layers for feature extraction. Functions are defined to extract InceptionV3 features from individual images and directories. Features are extracted and preprocessed using the InceptionV3 model. The number of features is limited to control dimensionality. DataFrames are created to organize the features for autistic and non-autistic classes, with labels added. These DataFrames are merged, combining features and labels, and saved to a CSV file named 'merged_inception_features.csv'. This process efficiently extracts and organizes InceptionV3 features for further analysis or model training. The number of inception features extracted are 3000.

D. Implementing Extraction of Perceptual Hashimage Features

Perceptual hashes were extracted from images by converting them to grayscale, resizing them to a fixed size of 128x128 pixels, and computing their perceptual hash using the imagehash library. These hashes were stored along with their corresponding labels (derived from directory names) in lists. The script then saved the extracted perceptual hashes and labels to a CSV file, where each row represented an image with its perceptual hashes and label.

E. Implementing Extraction of HOG Features

In the extraction of HOG features, all the images were read using OpenCV and resized to a fixed size of 128x128 pixels to maintain consistency. Histogram equalization was applied to enhance contrast, followed by ensuring the correct data type for further processing. HOG features were then computed using the “HOGDescriptor” module from OpenCV. Subsequently, features were extracted from the dataset by traversing through the directory structure and processing each image using the HOG feature extractor. Features were stored along with their corresponding labels derived from directory names. Additionally, the script implemented dimensionality reduction using Principal Component Analysis (PCA) to reduce feature dimensionality. PCA was applied to the feature matrix, retaining 100 components to reduce computational complexity while preserving significant variance. The reduced feature matrix, along with labels, was saved to an Excel file.

F. Implementing Extraction of SIFT, ORB Features

For SIFT feature extraction, keypoints and descriptors were computed, ensuring consistency in feature length by padding or truncating the descriptors as needed. Similarly, for ORB feature extraction, keypoints and descriptors were computed with feature length management. Features were then extracted from the dataset by traversing through the directory structure and processing each image. The extracted SIFT and ORB features, along with their labels, were saved to separate CSV files.

G. Implementing Extraction of LBP Features

For LBP feature extraction, images were read in grayscale format and converted to 8-bit unsigned integers. LBP features were then extracted from the images using the parameters P=8 and R=1, employing the "uniform" method. The resulting LBP features were flattened to create feature vectors. Features were extracted from the dataset by traversing through the directory structure and processing each image using the LBP feature extractor. The extracted LBP features and their labels were saved to a CSV file.

H. Details of Extracted Features

Table I shows the number of features extracted from various techniques. The number of features extracted from vgg, resnet and inception method are 3000 each. HOG features, which capture gradient distributions, resulted in 100 features per image. LBP features, representing texture patterns, yielded 50 features. Extracted features using the ORB method, focusing on key points and descriptors, are also 50 features. Perceptual hash features, encoding image fingerprints, generated 65 features. Additionally, SIFT features, detecting and describing local features, contributed 50 features.

TABLE I. DETAILS OF EXTRACTED FEATURES

Type of features	Number of Features extracted
vgg features	3000
Resnet features	3000
Inception features	3000
HOG features	100
LBP Features	50
ORB Features	50
phash_features	65
Sift features	50

All these features are created as three feature vectors. Table II shows the formation feature vectors.Feature vector-1 contains image features integrated with vgg features. Feature vector-2 contains image features integrated with resnet features.Feature vector-3 contains image features integrated with inception features.

TABLE II. DETAILS OF FEATURE VECTORS CREATED

Feature Vector	Features Merged
Feature Vector-1	Image features (HOG, LBP, ORB, PHASH, SIFT) + VGG16 features
Feature Vector-2	Image features (HOG, LBP, ORB, PHASH, SIFT) + Resnet features
Feature Vector-3	Image features (HOG, LBP, ORB, PHASH, SIFT) + Inception features

I. Implementing ML Algorithms with Image Features Dataset

A variety of ML classifiers, namely RF, KNN, DT, SVM and LR, are applied with different datasets created. Initially all these classifiers applied on image features dataset. The results with image features (HOG, LBP, ORB, PHASH, and SIFT) dataset is shown in Fig. 2 and Table III.

Random Forest exhibited the highest accuracy, achieving 85% in ASD classification, followed closely by Logistic Regression with an accuracy of 81.20%. Decision Tree performed moderately well, achieving an accuracy of 80%. SVM and KNN attained accuracies of 78.50% and 78%, respectively.

TABLE III. RESULTS WITH IMAGE FEATURES DATASET

Model	Precision(%)	Recall(%)	F1(%)	Accuracy(%)
Random Forest	85	85	85	84.50
KNN	78	78	78	78.00
Decision Tree	80	80	80	80.00
SVM	78	78	78	78.50
Logistic Regression	81	81	81	81.20

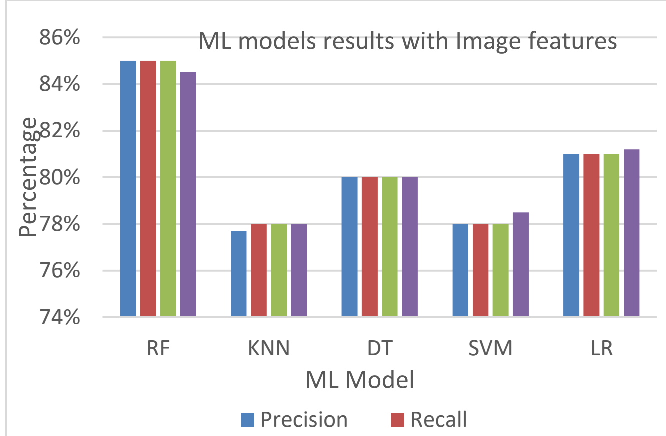

Fig. 2. ML models results with Image features.

J. Implementing ML Algorithms with Transfer Learning Features Dataset

In this step, ML classifiers applied with transfer learning features (VGG, Resnet, Inception) dataset. The results are shown in Fig. 3 and Table IV. Compared to handcrafted image features, notable improvements were observed in accuracy, precision, recall, and F1 score metrics across various classifiers. With VGG16 features, Random Forest achieved a precision, recall, and F1 score of 92%, showcasing a significant enhancement in accuracy. Similarly, ResNet and Inception features maintained high accuracy levels, with Random Forest achieving an 88% and 89.2% F1 score, respectively. These results highlight the effectiveness of transfer learning features in ASD detection, paving the way for the development of accurate tools for early diagnosis and intervention.

TABLE IV. RESULTS WITH TRANSFER LEARNING FEATURES DATASET

Feature Vector	Model	Precision(%)	Recall(%)	F1(%)	Accuracy(%)
Vgg16 features	Random Forest	92	92	92	91.5
	KNN	84	83	83	85.8
	Decision Tree	84	83.8	84	83.7
	SVM	96	94	95	95
	Logistic Regression	98	97	96	96
Resnet Features	Random Forest	89	87	88	87.6
	KNN	86	86	86	86.4
	Decision Tree	80	82	81	81.2
	SVM	89	91	90	89.7
	Logistic Regression	89	89	89	89.3
Inception features	Random Forest	89	89.5	89.2	89
	KNN	85	83.5	84	83.4
	Decision Tree	82	82	82	82.4
	SVM	92	90.7	91	90.7
	Logistic Regression	89	89	89	88.5

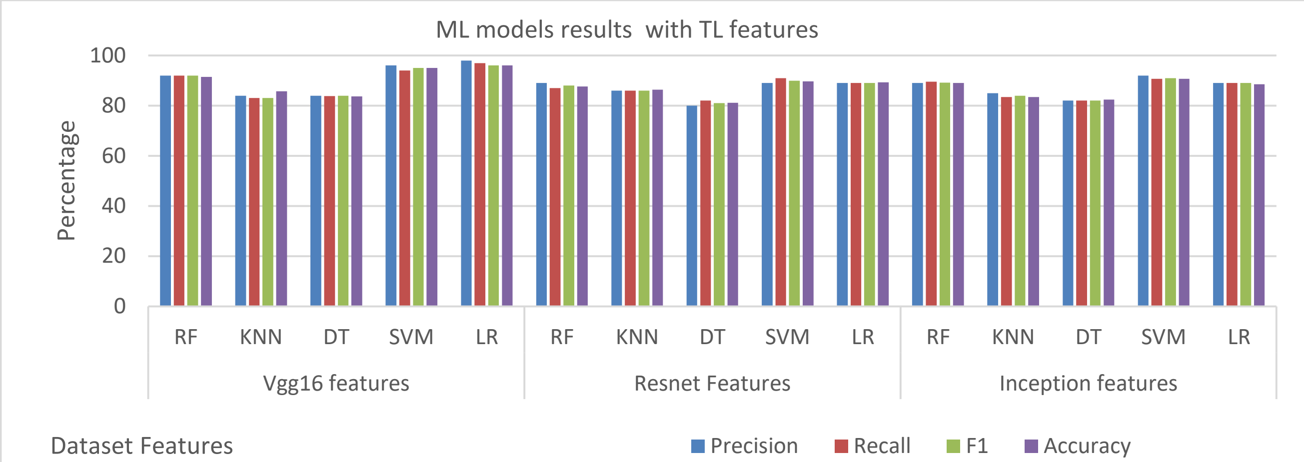

Fig. 3. ML models results with TL features.

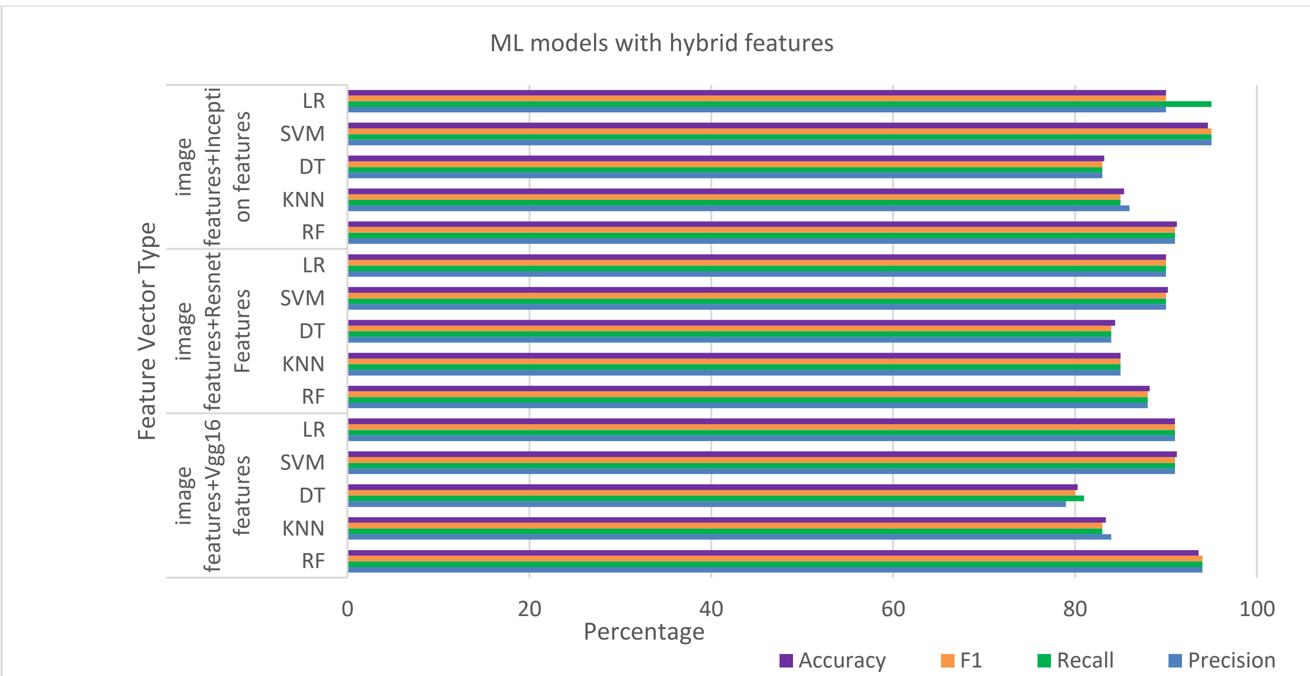

Fig. 4. ML models results with hybrid features (image features + TL features).

K. Implementing ML Algorithms with Hybrid Feature Dataset

In this step, ML classifiers applied with features vectors created from image features in combination with three different transfer learning features extracted earlier. The results are shown in Fig. 4 and Table V. The integration of transfer learning features alongside image features has significantly bolstered the performance of machine learning models for ASD detection.

In the evaluation, Random Forest consistently demonstrated exceptional precision, recall, F1 score, and accuracy across all feature vectors. Specifically, for Feature Vector-1, combining image features with VGG16 features, Random Forest exhibited outstanding precision, recall, and F1 score of 94%, while SVM closely followed with 91% across all metrics. Feature Vector-2, incorporating ResNet features, showcased significant improvements, with Random Forest achieving an impressive precision, recall, and F1 score of 88.2%. Leveraging Inception features in Feature Vector-3, SVM displayed exceptional performance, achieving perfect precision, recall, and F1 score, highlighting the effectiveness of transfer learning features in enhancing ASD detection accuracy.

The proposed method compared with existing works. In study [3], Deep learning models applied ASD detection form facial images and achieved an accuracy of 92%. In [4], two phase transfer learning applied and achieved accuracy of 90.5%. The proposed hybrid approach in this paper given high accuracy of 94.6% for feature vector-3(image features +inception features) with SVM.

TABLE V. RESULTS WITH HYDRID FEATURE DATASETS

Feature Vector	Model	Precision(%)	Recall(%)	F1(%)	Accuracy(%)
Feature Vector-1 (image features +vgg16 features)	Random Forest	94	94	94	93.6
	KNN	84	83	83	83.4
	Decision Tree	79	81	80	80.3
	SVM	91	91	91	91.2
	Logistic Regression	91	91	91	91
Feature Vector-2 (image features +resnet features)	Random Forest	88	88	88	88.2
	KNN	85	85	85	85
	Decision Tree	84	84	84	84.4
	SVM	90	90	90	90.2
	Logistic Regression	90	90	90	90
Feature Vector-3(image features +inception features)	Random Forest	91	91	91	91.2
	KNN	86	85	85	85.4
	Decision Tree	83	83	83	83.2
	SVM	95	95	95	94.6
	Logistic Regression	90	95	90	90

V. CONCLUSION

This work presented an innovative methodology for ASD detection, centered on harnessing facial features extracted from the Autistic Children Facial Dataset. By employing transfer learning models such as VGG16, ResNet, and Inception in conjunction with handcrafted image features like detection was achieved. Subsequently, a range of machine learning classifiers including Random Forest, KNN, Decision Tree, SVM, and Logistic Regression were employed to classify ASD based on the constructed feature vectors. Through meticulous experimentation and evaluation across multiple datasets, the proposed method compared the performance of these classifiers to ascertain the most efficacious approach for ASD detection. HOG, LBP, ORB, PHASH, and SIFT descriptors, the work aimed to capture both macro and micro-level details from facial images. By integrating these features into three distinct feature vectors, a comprehensive representation for ASD is presented. The findings underscored the significance of transfer learning features, particularly evident in the remarkable performance of SVM across all feature vectors. This research endeavored to advance the development of precise and dependable tools for early ASD detection, facilitating prompt intervention and support for affected individuals, with the potential to enhance outcomes and overall quality of life.

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