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Facial-Based Autism Classification Using Support Vector Machine Method

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Abstract: Autism Spectrum Disorder (ASD) is a complex neural developmental condition characterized by difficulties in communication, social interaction, and delayed brain development. Despite previous studies, there is a need to explore and enhance autism classification techniques using facial data. This research aims to classify individuals with autism based on facial images using the Support Vector Machine (SVM) method. It also evaluates the performance of SVM-based classification with HOG and SURF feature extraction, contributing to the identification of autism through facial features. A dataset of 200 facial images of students, including individuals with and without autism, was analyzed. The data was divided into 80:20 and 70:30 splits for training and testing purposes. SVM models with HOG and SURF feature extractions were evaluated using accuracy, precision, recall, and F1-Score metrics. The HOG-SVM and SURF-SVM models showed consistent performance in both data splitting scenarios. Accuracy values exceeded 0.88, and precision, recall, and F1-Score values were above 0.9. The 80:20 data split demonstrated improved performance, especially for the HOG-SVM model. Both HOG and SURF feature extraction methods showed good performance in classifying autism data. The SVM model with HOG achieved an accuracy of 0.95 in the 80:20 data split, while the SURF model achieved 0.9. Early autism detection based on facial data holds potential for use in student selection in elementary schools. However, the study has limitations due to limited data and the focus on accuracy alone. Future research can expand the data size, explore other feature extraction methods, and implement advanced deep learning techniques to improve classification performance and contribute further to autism detection based on facial data .

Keywords: Autism, HOG, SURF, SVM

1. Introduction

Autism was first described by Kanner in 1943, as a disorder characterized by difficulties in communication and interacting with others, along with a sense of indifference towards the outside world [1][2]. Autism Spectrum Disorder (ASD) leads to delayed brain development and affects its normal functioning[3]. This neural developmental condition is complex and hereditary. The prevalence of autism spectrum disorders (ASD) in South Asia varies, with prevalence rates ranging from 0.09% in India to 1.07% in Sri Lanka. This suggests that up to one in 93 children may have ASD in this region. Globally, the prevalence rate of ASD reaches approximately 1% to 2% of the overall population[4]. Autism is typically diagnosed around the age of 8, and its symptoms can vary depending on individual characteristics such as gender and other considerations. Approximately 25% of individuals with autism also experience intellectual disabilities, defined by an IQ below 70 [5][6].

Numerous studies have explored the utilization of diverse Machine Learning (ML) techniques for diagnosing and managing Autism Spectrum Disorder (ASD). Bala et al [7] introduced a ML system designed to enhance ASD identification across various age brackets. Employing distinct classification methodologies on their dataset, they identified Support Vector Machine (SVM) as particularly adept in ASD data classification. Furthermore, they integrated Shapley Additive Explanations (SHAPs) to pinpoint the most precise features crucial to the classification process. In another study[8], researchers utilized machine learning in conjunction with functional magnetic resonance imaging to pinpoint potential ASD indicators. They utilized ADOS scores as a severity gauge, discovering functional variances in the cingulum region with an accuracy of 73.8%. Hasan et all [9] showcased an effective ML evaluation methodology for early ASD detection. By employing four Attribute Scaling (AS) techniques and eight fundamental yet potent ML algorithms on the feature-scaled dataset, they achieved noteworthy accuracy rates. Adaptive Boosting (AB) and Linear Discriminant Analysis (LDA) emerged as the top

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performers, achieving 99.25% and 97.95% accuracy rates for toddlers and children, and 99.03% and 97.12% for adult and adolescent datasets, respectively. The framework proposed by Raj et al [10] Implementing several machine learning algorithms, the predictive model based on Convolutional Neural Network (CNN) achieved high accuracy in screening Autism Spectrum Disorder (ASD), with an accuracy of 99.53%, followed by K-Nearest Neighbors (KNN) with an accuracy of 70%, followed by SVM with an accuracy of 65%, and Random Forest with an accuracy of 63%.

In another study, Petrucci et al[11] collected 959 data samples from 8 different projects and then employed machine learning techniques such as Random Forest (RF), Gradient Boosting Machine (GBM), and Support Vector Machine (SVM) to predict Autism Spectrum Disorder (ASD) and healthy control conditions. They investigated the crucial role of gut microbiota in autism spectrum disorders and found that all three algorithms indicated significant importance of the genera Parasutterella and Alloprevotella in the prediction. Study[12] employed the Gradient Boosting method to classify the diagnosis status of children, comprising 35 children with Autism Spectrum Disorder (ASD) and 35 children with typical development (TD). The research achieved an accuracy of 75.71% in identifying the diagnosis status of the children. For children with typical development, the accuracy reached 85.71% (30 out of 35 children), whereas for children with ASD, the accuracy decreased to 65.71% (23 out of 35 children). Furthermore, Omar [13] proposed an ML-based ASD prediction model and developed a mobile application suitable for all age groups. This research resulted in a predictive model for autism and a mobile application that integrated Random Forest with Classification And Regression Tree (CART) as well as Random Forest with Iterative Dichotomiser 3 (ID3). The model was tested using 250 real-world datasets from individuals with and without autism.

In another study [14], the objective was to identify the best machine learning methods for classifying ASD using various algorithms, including Random Forest, SVM, Stochastic Gradient Descent (SGD), KNN, Naïve Bayes, Adaptive Boosting (AdaBoost), Objective, and CN2 Rule. The research utilized datasets from the UCI repository, covering data for adult children, adolescents, young children, and toddlers. The findings demonstrated the highest accuracies for different datasets, with SGD adult dataset reaching 99.7%, RF adolescent dataset reaching 97.2%, young children dataset achieving 99.6% accuracy, SGD children dataset obtaining 99.6% accuracy, and AdaBoost achieving 99.8% accuracy for the toddler dataset.

In the previous study conducted by Muhathir et al[15], it was found that the autism classification model based on facial data using the Naive Bayes classification method with the assistance of Histogram of Oriented Gradient (HOG) feature extraction achieved highly satisfactory performance. The study utilized a total of 200 data, with 80% used for training and 20% for testing the model. The Naive Bayes model was tested with three variations: Bernoulli, Multinomial, and Gaussian. The evaluation results showed that the Naive Bayes model with the Bernoulli variation achieved the highest accuracy of 89.72%, while the model with the Multinomial variation demonstrated good performance with an accuracy of 89.47%. However, the model with the Gaussian variation showed lower accuracy, reaching only 65.91%.

Numerous prior investigations have focused on autism classification utilizing various data sources such as questionnaires, brain scans, ASD screening, and facial data, drawing upon existing research. Thus, our study endeavors to construct a machine learning model aimed at categorizing children with autism through facial image analysis. The chosen methodology involves employing Support Vector Machine (SVM), augmented by Speed Up Robust Feature (SURF) and Histogram of Oriented Gradient (HOG) feature extraction techniques.

Support Vector Machine (SVM) is a powerful method for data analysis and pattern recognition, commonly used for classification tasks that require labeled data[16][17]. It offers advantages such as clear concept, adaptability to multiple parameters, the ability to generate effective classification models even with relatively small datasets and simple parameter settings. SVM has a well-defined formulation and can be easily implemented through Quadratic Programming problems [18], [19], [20].

The Histogram of Oriented Gradient (HOG) is a widely adopted feature descriptor employed in computer vision for object detection and recognition tasks. This technique involves computing the magnitude and orientation of gradients for each pixel, typically utilizing operators like the Sobel operator or other edge detection algorithms. Subsequently, the distribution of oriented gradients in neighboring cells is normalized, and amalgamated into a unified feature vector. This process facilitates the extraction of distinctive features essential for robust object detection and recognition, making HOG a prominent choice in the field of computer vision. [21], [22], [23].

SURF (Speeded-Up Robust Features) represents an enhanced iteration of the Scale-Invariant Feature Transform (SIFT), renowned for its scale-invariant feature transformation capabilities. Notably, SURF boasts a notable improvement in speed, performing 3-5 times faster than its predecessor, SIFT. The SURF algorithm unfolds in two primary steps: feature extraction and feature description, rendering it a pivotal tool in various practical applications such as scene comprehension and surveillance. Notably, SURF leverages box filters to swiftly compute operators, underscoring its efficiency in processing visual data.[24], [25], [26].

Despite the numerous studies conducted previously,

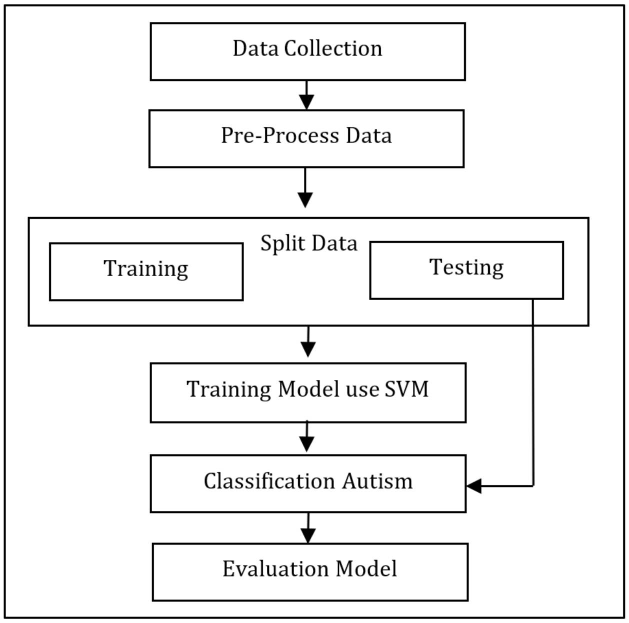


Figure 1. Research Architecture
[27]

there is still a need to explore and enhance autism classification techniques using facial data. Therefore, this research aims to contribute to existing knowledge by utilizing the feature extraction techniques HOG and SURF in the process of obtaining information from facial data, along with the SVM classification method to identify facial images displaying characteristics of autism.

The explicit objectives of this study are as follows: 1. To contribute to the identification of autism through relevant facial feature analysis, particularly in the context of facial patterns of children in the North Sumatra region, Indonesia.

2. To classify individuals with autism based on facial images using the Support Vector Machine (SVM) method.

3. To evaluate the performance of the SVM-based classification approach, considering the proposed assistance of HOG and SURF feature extraction in this study.

2. Methods

A. Research Architecture

The research framework depicted in Figure 1 outlines the methodology employed in this study for classifying autism using facial images. The research workflow initiates with data acquisition, followed by meticulous preprocessing to curate a dataset comprising pertinent image samples. This dataset is then partitioned into training and testing subsets. Support Vector Machine (SVM) is leveraged to construct a robust classification model, trained on the designated training data. Subsequently, the testing data is utilized to classify images by evaluating the similarity or likeness of weight patterns derived from the trained model, thus yielding classification results. To evaluate the model's performance, Equations 1-4 are applied to calculate key metrics including accuracy, precision, recall, and F1-score. Lastly, the model's efficacy is validated by testing it on an independent dataset. This meticulous approach ensures the robustness and validity of the developed classification model for detecting autism based on facial images.

B. Data collection and Preprocessing data

In this study, data collection involved employing a smartphone camera positioned approximately 100cm away from the subjects. The procedure commenced with the preparation of necessary equipment, notably a high-quality smartphone equipped with a camera. Ensuring adequate lighting conditions around the subjects was prioritized to guarantee optimal illumination. Subsequently, the distance between the smartphone camera and the subjects was meticulously set at approximately 100cm to facilitate precise focusing and capture detailed images. To mitigate perspective distortion, the smartphone camera was aligned parallel to the subjects. Additionally, adjustments were made to the camera settings, including image resolution and mode selection, as deemed necessary. Throughout the photo-taking process, care was taken to direct the smartphone camera towards the subjects without obstructing light or objects with hands or fingers. Rigorous examination of the captured photos ensued to verify clarity and detailed depiction of the subjects' images. Hence, employing a smartphone camera at a 100cm distance facilitated ample data collection, laying a strong foundation for subsequent analysis.

Upon gathering the facial image data of students through smartphone photography, the subsequent crucial phase entails data preprocessing to adequately prepare it for further analysis. This preprocessing endeavor involves several pivotal stages. Initially, adjustments are made to the format and resolution of the images to align with the analysis requirements. This encompasses resizing the images, refining file formats, and enhancing image clarity to ensure optimal data quality. Throughout this preprocessing phase, diligent efforts are undertaken to mitigate any noise or disturbances present within the images. If necessary, any interfering elements such as shadows or artifacts are meticulously eliminated. By meticulously adhering to the preprocessing procedures, the facial image data of the students is meticulously refined, rendering it ready for subsequent analysis phases, such as pattern recognition and classification of facial patterns. This meticulous and comprehensive preprocessing ensures the reliability and utmost quality of the data intended for utilization in this study.

C. Data Analysis

In the data analysis phase of this study, we utilized a dataset comprising 200 facial images of students, encompassing two distinct student groups. To ensure comprehensive evaluation, the dataset was evenly partitioned for both training and testing purposes. Under the 80:20 data split configuration, 80% of the dataset was allocated for model training, while the remaining 20% was designated for testing. Conversely, in the 70:30 data split scenario, 70% of the dataset was utilized for training, with the remaining 30% reserved for testing purposes. This systematic division was imperative to foster a balanced representation of diverse student characteristics within the dataset and mitigate potential biases in the analysis process. Consequently, this meticulous approach to data analysis underpins the robustness of our research outcomes and validates the results derived from the developed model.

D. Performa Measure

The confusion matrix serves as a valuable tool for evaluating the effectiveness of an object estimation model. It enables a comprehensive comparison between the model's predicted classifications and the actual classes, providing detailed insights into the model's performance[28]. Accuracy, as a metric, indicates the alignment of predicted values with the true values. Precision measures the consistency of the model's predictions or the proportion of accurate positive predictions. On the other hand, recall reflects the model's ability to identify correct positive responses. By combining precision and recall, the f1-score offers a balanced and overall assessment of the model's performance. These metrics are essential for assessing the model's performance, as they offer a quantitative and objective measure of its accuracy and reliability. The formulas used to calculate these metrics are based on the true positive (TP_{autism}), true negative (TN_{autism}), false positive (FP_{autism}), and false negative (FN_{autism}) values, which represent the number of correctly identified positive cases, correctly identified negative cases, incorrectly identified positive cases, and incorrectly identified negative cases, respectively[29].

Description

$$Accuracy = \frac{TN_{autism}+TP_{autism}}{TN_{autism}+FP_{autism}+TP_{autism}+FN_{autism}} \quad (1)$$

$$Precision = \frac{TP_{autism}}{FP_{autism}+TP_{autism}} \quad (2)$$

$$Recall = \frac{TP_{autism}}{TP_{autism}+FN_{autism}} \quad (3)$$

$$F1 - Score = \frac{2*Precision*Recall}{Precision+Recall} \quad (4)$$

3. Results

This research aims to examine the performance of the Support Vector Machine (SVM) classification method in the case of autism data classification through facial images. The testing is conducted with two different scenarios to understand how SVM's performance varies with different data divisions. In each scenario, we will test two feature extraction methods, namely Histogram of Oriented Gradients (HOG) and Speeded-Up Robust Features (SURF). The first scenario's objective is to evaluate how SVM's performance changes with different proportions of training and test data. We want to determine whether these changes in data division affect the accuracy and overall performance of the SVM model. Additionally, by comparing the results from HOG and SURF feature extraction, we aim to determine which feature extraction method is more effective in classifying autism data.

Through this testing, the research aims to provide a deeper understanding of SVM's use in autism data classification and offer guidance in selecting optimal SVM parameters and feature extraction methods. The expected outcome of this research is to contribute to the development of image classification applications in the medical and healthcare fields, particularly in early detection and diagnosis of autism. Thus, the study is expected to bring benefits to efforts in enhancing the understanding and early management of autism through facial data analysis.

SVM testing parameters using RBF kernel with gamma value of 0.1 and C value of 1.0 have been determined. Next, to perform model tuning using GridSearchCV or RandomizedSearchCV techniques, we set up param_grid with several different values. This param_grid includes a variety of values param_grid = {'C': [0.1, 1, 10, 100], 'gamma': [0.001, 0.01, 0.1, 1], 'kernel': ['linear', 'rbf', 'poly']}. By tuning the combination of these values, we aim to find the optimal configuration for the SVM model that allows us to maximize the model's performance and generalization to the given dataset. Using this technique, we hope to find the right parameters that result in an SVM model with optimal accuracy in solving a given classification task.

A. Sample Data

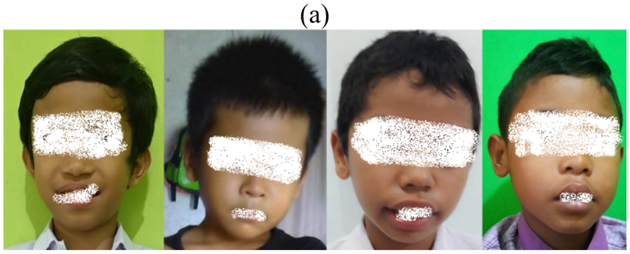
Below is an overview of the dataset used in this research. This dataset consists of two main types of data, namely facial data of normal children and facial data of children with autism. Each type of data contains facial images collected from different groups of children. The facial data of normal children includes images of children without neurological disorders or significant developmental issues. Meanwhile, the facial data of children with autism contains images of children diagnosed with autism spectrum disorder. The purpose of this dataset is to support analysis and modelling to identify distinctive features and patterns that differentiate between normal children's faces and faces of children with autism. The use of this dataset aims to enhance the understanding of autism and potentially assist in early detection and more appropriate treatment for children experiencing autism spectrum disorder.

B. Feature Detection

Feature detection is a crucial step in analyzing facial images of children, particularly those with autism, to extract relevant information for further analysis. In this study, we focus on two feature detection techniques: Histogram of Oriented Gradients (HOG) and Speeded-Up Robust Features (SURF).

- 3(a) Facial Image of Children with Autism: The input image (a) represents a facial image of a child

(a)



(b)

Figure 2. Children's face (a) Normal (b) Autistic

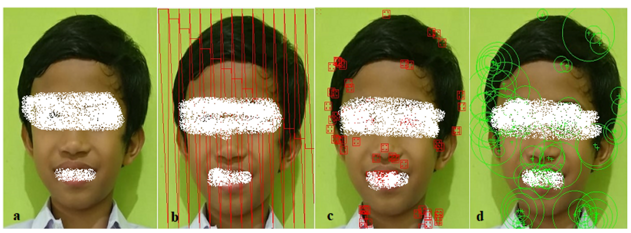


Figure 3. Feature Detection Process (a) Facial Image of Children with Autism, (b) Grid 8x8 Processing for HOG and SURF, (c) HOG Detection with Marked Boxes, and (d) SURF Detection with Blob Marking

diagnosed with autism. This raw image is the starting point for feature detection.

- 3(b) Grid 8x8 Processing: In both HOG and SURF techniques, the image is divided into an 8x8 grid. For HOG, each cell within the grid calculates local gradients and directions, capturing the intensity and orientation of edges within that region. Similarly, in SURF, the 8x8 grid is utilized to detect interest points (blobs) that are invariant to scale and rotation. This grid-based processing enables both algorithms to extract distinctive local features from different regions of the facial image.
- 3(c) HOG Detection with Marked Boxes: The HOG algorithm processes the 8x8 grid and extracts relevant features, which are then represented as a descriptor vector. The descriptor vectors are used to highlight specific regions of interest in the facial image. These regions are marked with bounding boxes, indicating the detected features.
- 3(d) SURF Detection with Blob Marking: On the other hand, the SURF technique identifies interest points (blobs) in the facial image that are invariant to scale and rotation. These key points are detected using an integral image representation, allowing the SURF algorithm to locate and mark relevant features with circular blobs.

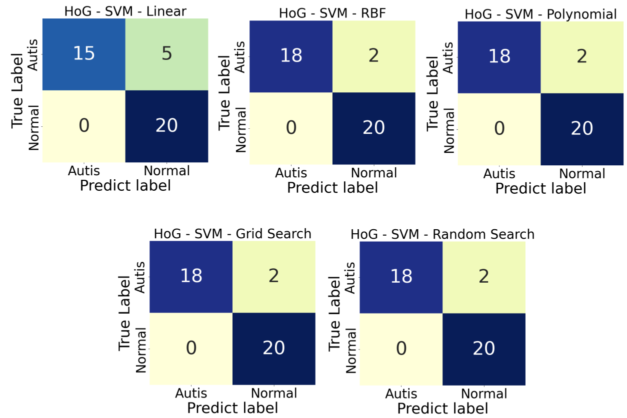


Figure 4. The confusion matrix results of the models (top left) HOG-SVM-Linear, (top center) HOG- SVM-RBF, (top right) HOG- SVM-Polynomial, (bottom left) HOG-SVM-Grid Search, and (bottom right) HOG-SVM-Random Search

Both HOG and SURF techniques contribute to the characterization of distinctive facial features in children with autism. These detected features provide valuable information for subsequent analysis, aiding in the understanding and potential diagnosis of autism spectrum disorder

C. Scenario 1 Split data 80:20

1) The results of the testing with the HOG feature extraction

The HOG feature extraction results in the 80:20 data split scenario show the performance variation of the five different experimental models. Furthermore, the SVM classification results with kernel variations and model tuning search are presented in Figure 4, Table I presents the attempt to find the optimal parameters to improve the performance of the SVM model in this classification task.

In the HOG - SVM - Linear model, it achieved satisfactory performance in correctly recognizing normal faces, where all 20 normal faces were classified accurately without any errors. However, the performance of this model was not satisfactory in recognizing autistic faces, as only 15 autistic faces were correctly classified, while 5 autistic faces were misclassified as normal faces. The same exact results were obtained in the other four models, namely HOG - SVM - RBF, HOG - SVM - Polynomial, HOG - SVM - Grid Search, and HOG - SVM - Random Search. In these four models, all 20 normal faces were correctly identified, but only 2 autistic faces were misclassified as normal faces, while the remaining 18 autistic faces were classified correctly. The performance evaluation results are presented in Table II The evaluation results indicate that the HOG - SVM - Linear model has good performance but slightly

TABLE I. Hyperparameter Tuning SVM with HOG Feature Extraction In Scenario 1

Grid Search	Random Search
Combination 1: 'C': 0.1, 'gamma': 0.001, 'kernel': 'linear', Score: 0.725 Combination 2: 'C': 0.1, 'gamma': 0.001, 'kernel': 'rbf', Score: 0.71875 Combination 3: 'C': 0.1, 'gamma': 0.001, 'kernel': 'poly', Score: 0.85 Combination 4: 'C': 0.1, 'gamma': 0.01, 'kernel': 'linear', Score: 0.725 ... Combination 46: 'C': 100, 'gamma': 1, 'kernel': 'linear', Score: 0.8 Combination 47: 'C': 100, 'gamma': 1, 'kernel': 'rbf', Score: 0.85 Combination 48: 'C': 100, 'gamma': 1, 'kernel': 'poly', Score: 0.825 Best Hyperparameters: 'C': 1, 'gamma': 1, 'kernel': 'poly' Best CV Score: 0.86875	Combination 1: 'C': 3.5636385764965555, 'gamma': 0.9479626038148141, 'kernel': 'rbf', Score: 0.875 Combination 2: 'C': 22.132909956078095, 'gamma': 0.5749083828109902, 'kernel': 'rbf', Score: 0.84375 Combination 3: 'C': 0.3172616724554296, 'gamma': 0.39344246646503067, 'kernel': 'poly', Score: 0.85 Combination 4: 'C': 31.624035914755126, 'gamma': 0.42776536740709004, 'kernel': 'poly', Score: 0.8625 ... Combination 8: 'C': 0.730808050593054, 'gamma': 0.823466339103433, 'kernel': 'rbf', Score: 0.84375 Combination 9: 'C': 0.21450288700004144, 'gamma': 0.0015288111692760556, 'kernel': 'rbf', Score: 0.71875 Combination 10: 'C': 0.3285128275180457, 'gamma': 0.21315342299339557, 'kernel': 'poly', Score: 0.85 Best Hyperparameters: 'C': 3.5636385764965555, 'gamma': 0.9479626038148141, 'kernel': 'rbf' Best CV Score: 0.875

TABLE II. The performance evaluation of HOG feature extraction and SVM in scenario 1

Model	Accuracy	Precision	Recall	F1-Score
Hog – SVM – Linear	0.88	0.90	0.88	0.87
Hog – SVM – RBF	0.95	0.95	0.95	0.95
Hog – SVM – Polynomial	0.95	0.95	0.95	0.95
Hog – SVM – Grid Search	0.95	0.95	0.95	0.95
Hog – SVM – Random Search	0.95	0.95	0.95	0.95

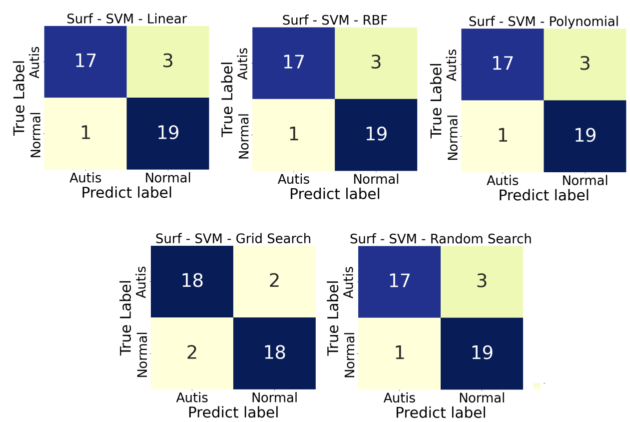


Figure 5. The confusion matrix results of the models (top left) SURF-SVM-Linear, (top center) SURF- SVM-RBF, (top right) SURF- SVM-Polynomial, (bottom left) SURF-SVM-Grid Search, and (bottom right) SURF-SVM-Random Search

below the other models. The performance evaluation of the classification models with HOG feature extraction and SVM shows excellent results. The HOG - SVM - RBF, HOG - SVM - Polynomial, HOG - SVM - Grid Search, and HOG - SVM - Random Search models all have accuracy, precision, recall, and F1-Score values of 0.95. These values indicate that all models have high capabilities in accurately classifying data with a good balance between precision and recall. Overall, these findings demonstrate the potential application of these models in supporting efficient and accurate detection and classification of autistic data.

2) The results of the testing with the SURF feature extraction

The SURF feature extraction results in the 80:20 data split scenario show the performance variation of the five different experimental models. Furthermore, the SVM classification results with kernel variations and model tuning search are presented in Figure 5, Table III presents the attempt to find the optimal parameters to improve the performance of the SVM model in this classification task.

The results of testing with SURF feature extraction in the 80:20 scenario show variations in the performance of five similar experimental models. The SURF - SVM - Grid Search model successfully recognizes normal and autistic faces well, correctly classifying 18 normal faces and 18 autistic faces. However, there are 2 normal faces that are misclassified as autistic and 2 autistic faces that are misclassified as normal. Similar results are obtained in the other four models, namely SURF - SVM - Linear, SURF - SVM - RBF, SURF - SVM - Polynomial, and SURF - SVM

TABLE III. Hyperparameter Tuning SVM with SURF Feature Extraction In Scenario 1

Grid Search	Random Search
Combination 1: 'C': 0.1, 'gamma': 0.001, 'kernel': 'linear', Score: 0.825	Combination 1: 'C': 3.5636385764965555, 'gamma': 0.9479626038148141, 'kernel': 'rbf', Score: 0.86875
Combination 2: 'C': 0.1, 'gamma': 0.001, 'kernel': 'rbf', Score: 0.80625	Combination 2: 'C': 22.132909956078095, 'gamma': 0.5749083828109902, 'kernel': 'rbf', Score: 0.84375
Combination 3: 'C': 0.1, 'gamma': 0.001, 'kernel': 'poly', Score: 0.85625	Combination 3: 'C': 0.3172616724554296, 'gamma': 0.39344246646503067, 'kernel': 'poly', Score: 0.85625
Combination 4: 'C': 0.1, 'gamma': 0.01, 'kernel': 'linear', Score: 0.825	Combination 4: 'C': 31.624035914755126, 'gamma': 0.42776536740709004, 'kernel': 'poly', Score: 0.88125
...	...
Combination 46: 'C': 100, 'gamma': 1, 'kernel': 'linear', Score: 0.79375	Combination 8: 'C': 0.730808050593054, 'gamma': 0.823466339103433, 'kernel': 'rbf', Score: 0.85625
Combination 47: 'C': 100, 'gamma': 1, 'kernel': 'rbf', Score: 0.8625	Combination 9: 'C': 0.21450288700004144, 'gamma': 0.0015288111692760556, 'kernel': 'rbf', Score: 0.80625
Combination 48: 'C': 100, 'gamma': 1, 'kernel': 'poly', Score: 0.88125	Combination 10: 'C': 0.3285128275180457, 'gamma': 0.21315342299339557, 'kernel': 'poly', Score: 0.85625
Best Hyperparameters: 'C': 0.1, 'gamma': 1, 'kernel': 'rbf'	Best Hyperparameters: 'C': 31.624035914755126, 'gamma': 0.42776536740709004, 'kernel': 'poly'
Best CV Score: 0.88125	Best CV Score: 0.88125

TABLE IV. The performance evaluation of SURF feature extraction and SVM in scenario 1

Model	Accuracy	Precision	Recall	F1-Score
Hog – SVM – Linear	0.9	0.9	0.9	0.9
Hog – SVM – RBF	0.9	0.9	0.9	0.9
Hog – SVM – Polynomial	0.9	0.9	0.9	0.9
Hog – SVM – Grid Search	0.9	0.9	0.9	0.9
Hog – SVM – Random Search	0.9	0.9	0.9	0.9

- Random Search. These four models correctly recognize 19 normal faces and 17 autistic faces. However, there is 1 normal face that is misclassified as autistic and 3 autistic faces that are incorrectly classified as normal. The performance evaluation results are presented in Table IV Testing SVM with SURF feature extraction shows overall uniqueness in the performance evaluation of the classification models. Throughout the testing, all experimental models, namely Surf - SVM - Linear, Surf - SVM - RBF, Surf - SVM - Polynomial, Surf - SVM - Grid Search, and Surf - SVM - Random Search, demonstrate consistent and similar results. All of these models have an accuracy, precision, recall, and F1-Score value of 0.9.

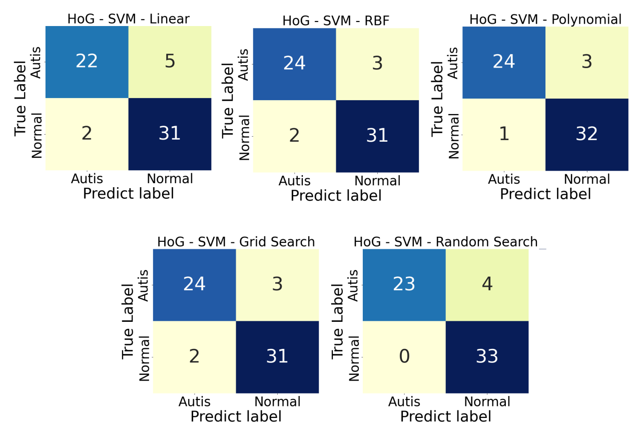


Figure 6. The confusion matrix results of the models (top left) HOG-SVM-Linear, (top center) HOG- SVM-RBF, (top right) HOG- SVM-Polynomial, (bottom left) HOG-SVM-Grid Search, and (bottom right) HOG-SVM-Random Search

D. Scenario 2 Split data 70:30

1) The results of the testing with the HOG feature extraction

The HOG feature extraction results in the 70:30 data split scenario show the performance variation of the five different experimental models. Furthermore, the SVM classification results with kernel variations and model tuning search are presented in Figure 6, Table V presents the attempt to find the optimal parameters to improve the performance of the SVM model in this classification task.

The HOG - SVM - Linear model correctly classifies 22 autistic data, but misidentifies 5 normal data as autistic. Additionally, the model accurately recognizes 31 normal data. The HOG - SVM - RBF model performs well in

TABLE V. Hyperparameter Tuning SVM with HOG Feature Extraction In Scenario 2

Grid Search	Random Search
Combination 1: 'C': 0.1, 'gamma': 0.001, 'kernel': 'linear', Score: 0.7571428571428571 Combination 2: 'C': 0.1, 'gamma': 0.001, 'kernel': 'rbf', Score: 0.5214285714285714 Combination 3: 'C': 0.1, 'gamma': 0.001, 'kernel': 'poly', Score: 0.5214285714285714 Combination 4: 'C': 0.1, 'gamma': 0.01, 'kernel': 'linear', Score: 0.7571428571428571 ... Combination 46: 'C': 100, 'gamma': 1, 'kernel': 'linear', Score: 0.7928571428571429 Combination 47: 'C': 100, 'gamma': 1, 'kernel': 'rbf', Score: 0.8857142857142858 Combination 48: 'C': 100, 'gamma': 1, 'kernel': 'poly', Score: 0.8928571428571429 Best Hyperparameters: 'C': 1, 'gamma': 1, 'kernel': 'poly' Best CV Score: 0.9	Combination 1: 'C': 3.5636385764965555, 'gamma': 0.94796260381, 'kernel': 'rbf', Score: 0.89285714285 Combination 2: 'C': 22.132909956078095, 'gamma': 0.57490838281, 'kernel': 'rbf', Score: 0.86428571428 Combination 3: 'C': 0.317261672455429, 'gamma': 0.3934424664, 'kernel': 'poly', Score: 0.5214285714 Combination 4: 'C': 31.624035914755, 'gamma': 0.427765367407, 'kernel': 'poly', Score: 0.88571428571428 ... Combination 8: 'C': 0.730808050593054, 'gamma': 0.8234663391, 'kernel': 'rbf', Score: 0.86428571428 Combination 9: 'C': 0.214502887000041, 'gamma': 0.001528811169, 'kernel': 'rbf', Score: 0.52142857142 Combination 10: 'C': 0.32851282751, 'gamma': 0.213153422993, 'kernel': 'poly', Score: 0.52142857142 Best Hyperparameters: 'C': 3.5636385764965555, 'gamma': 0.9479626038148141, 'kernel': 'rbf' Best CV Score: 0.8928571428571429

identifying autistic data, with 24 autistic data correctly classified and only 3 autistic data misclassified. The model also correctly identifies 31 normal data. The HOG - SVM - Polynomial model yields similar results to the RBF model, with 24 autistic data correctly classified and 3 autistic data misclassified. Moreover, the model accurately recognizes 32 normal data, with only 1 normal data misclassified. The HOG - SVM - Grid Search model also demonstrates similar performance to the RBF and Polynomial models, with 24 autistic data correctly classified and only 3 autistic data misclassified. The model correctly identifies 31 normal data. The HOG - SVM - Random Search model almost has a similar performance to the Grid Search model, with 23 autistic data correctly classified and 4 autistic data misclassified. All 33 normal data are correctly identified. The performance evaluation results are presented in Table VI

TABLE VI. The performance evaluation of HOG feature extraction and SVM in scenario 2

Model	Accuracy	Precision	Recall	F1-Score
Hog – SVM – Linear	0.88	0.88	0.88	0.88
Hog – SVM – RBF	0.92	0.92	0.92	0.92
Hog – SVM – Polynomial	0.93	0.93	0.93	0.93
Hog – SVM – Grid Search	0.92	0.92	0.92	0.92
Hog – SVM – Random Search	0.93	0.93	0.93	0.93

The evaluation results indicate that these models are capable of accurately and efficiently classifying autistic faces. Each model exhibits a good balance between precision and recall. Specifically, the Hog - SVM - RBF, Hog - SVM - Grid Search, Hog - SVM - Polynomial, and Hog - SVM - Random Search models achieve higher performance with an accuracy, precision, recall, and F1-Score of 0.92 and 0.93. However, the Hog - SVM - Linear model only achieves a performance with an accuracy, precision, recall, and F1-Score of 0.88.

2) The results of the testing with the SURF feature extraction

The SURF feature extraction results in the 70:30 data split scenario show the performance variation of the five different experimental models. Furthermore, the SVM classification results with kernel variations and model tuning search are presented in Figure 7, Table VII presents the attempt to find the optimal parameters to improve the performance of the SVM model in this classification task.

From the achievement of the classification results presented through the confusion matrix of the five HOG - SVM classification models using different kernel functions (Linear, RBF, and Polynomial) as well as Grid Search and Random Search implementations, it is observed that these models yield similar confusion matrix values. All of these models are capable of classifying autistic data effectively, with 24 autistic data being correctly classified,

TABLE VII. Hyperparameter Tuning SVM with SURF Feature Extraction In Scenario 2

Grid Search	Random Search
Combination 1: 'C': 0.1, 'gamma': 0.001, 'kernel': 'linear', Score: 0.7428571428571429 Combination 2: 'C': 0.1, 'gamma': 0.001, 'kernel': 'rbf', Score: 0.5214285714285714 Combination 3: 'C': 0.1, 'gamma': 0.001, 'kernel': 'poly', Score: 0.5214285714285714 Combination 4: 'C': 0.1, 'gamma': 0.01, 'kernel': 'linear', Score: 0.7428571428571429 ... Combination 46: 'C': 100, 'gamma': 1, 'kernel': 'linear', Score: 0.7499999999999999 Combination 47: 'C': 100, 'gamma': 1, 'kernel': 'rbf', Score: 0.8428571428571429 Combination 48: 'C': 100, 'gamma': 1, 'kernel': 'poly', Score: 0.8928571428571429 Best Hyperparameters: 'C': 1, 'gamma': 1, 'kernel': 'poly' Best CV Score: 0.9	Combination 1: 'C': 3.5636385764965555, 'gamma': 0.94796260381, 'kernel': 'rbf', Score: 0.85714285714 Combination 2: 'C': 22.132909956078095, 'gamma': 0.57490838281, 'kernel': 'rbf', Score: 0.8428571428 Combination 3: 'C': 0.3172616724554296, 'gamma': 0.39344246646, 'kernel': 'poly', Score: 0.52142857142 Combination 4: 'C': 31.624035914755126, 'gamma': 0.42776536740, 'kernel': 'poly', Score: 0.8785714285 ... Combination 8: 'C': 0.730808050593054, 'gamma': 0.8234663391, 'kernel': 'rbf', Score: 0.87857142857 Combination 9: 'C': 0.21450288700004144, 'gamma': 0.00152881116927, 'kernel': 'rbf', Score: 0.52142857142 Combination 10: 'C': 0.3285128275180457, 'gamma': 0.21315342299, 'kernel': 'poly', Score: 0.52142857142 Best Hyperparameters: 'C': 84.69631737532002, 'gamma': 0.4201212279977419, 'kernel': 'poly' Best CV Score: 0.8928571428571429

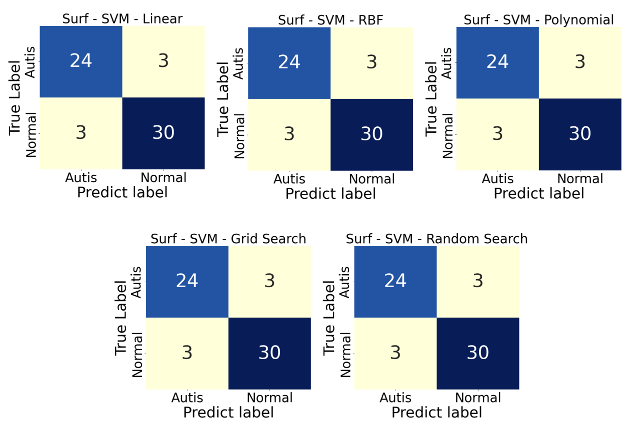


Figure 7. The confusion matrix results of the models (top left) SURF-SVM-Linear, (top center) SURF- SVM-RBF, (top right) SURF- SVM-Polynomial, (bottom left) SURF-SVM-Grid Search, and (bottom right) SURF-SVM-Random Search

and only 3 autistic data being misclassified. The models also perform well in recognizing normal data, with 30 normal data being correctly classified, and only 3 normal data being misclassified as autistic data. Overall, the HOG - SVM classification models demonstrate good performance in classifying autistic and normal data. Although there are some misclassifications, the overall prediction results are quite consistent and accurate. The performance evaluation results are presented in Table VIII The evaluation results indicate that all Surf - SVM classification models exhibit similar and consistent performance. The accuracy, precision, recall, and F1-Score values of all models are 0.9, indicating that these models successfully classify the data correctly with an accuracy of 90%.

TABLE VIII. The performance evaluation of SURF feature extraction and SVM in scenario 2

Model	Accuracy	Precision	Recall	F1-Score
Hog – SVM – Linear	0.9	0.9	0.9	0.9
Hog – SVM – RBF	0.9	0.9	0.9	0.9
Hog – SVM – Polynomial	0.9	0.9	0.9	0.9
Hog – SVM – Grid Search	0.9	0.9	0.9	0.9
Hog – SVM – Random Search	0.9	0.9	0.9	0.9

From the evaluation results, it can be observed that the performance of Surf - SVM and Hog - SVM classification models in both data splitting scenarios (70:30 and 80:20) shows similar and consistent outcomes. All models have accuracy values of 0.88 or higher, indicating their ability to correctly classify data with an accuracy of 88% or more. Similarly, the precision, recall, and F1-Score values of all models are 0.9 or higher, signifying their ability to recognize and predict data effectively. In the 70:30 data splitting scenario, the Hog - SVM model with RBF, Polynomial, Grid Search, and Random Search kernel functions shows an improvement in performance in the 80:20 scenario, where the accuracy increases from 0.92 to 0.95. This suggests that

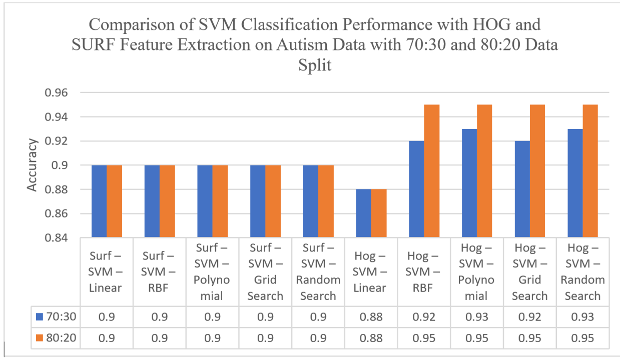


Figure 8. The confusion matrix results of the models (a) SVM-HOG-Linear, (b) SVM-HOG-RBF, and (c) SVM-HOG-Polynomial

the 80:20 data split contributes positively to the model's performance, possibly due to a larger training data size for learning. Conversely, the Surf - SVM model achieves consistent results between the 70:30 and 80:20 data splitting scenarios, indicating that the Surf feature extraction is more stable and less influenced by the data splitting. Overall, the evaluation results indicate that the Surf - SVM and Hog - SVM classification models exhibit good and consistent performance in both data splitting scenarios. The 80:20 data split tends to provide better performance than the 70:30 split. These models hold potential for application in early detection of new students with autism in elementary schools.

4. Discussion

The presented evaluation results indicate that the Surf - SVM and Hog - SVM classification models perform well and consistently in classifying autistic and normal data. With high accuracy, precision, recall, and F1-Score values (0.9 or higher), it can be concluded that these models perform well in predicting and classifying data correctly. These findings provide strong insights into the effectiveness and reliability of the implemented classification models with Surf and Hog feature extractions using SVM.

In the previous study conducted by [15], the findings showed that the autistic classification model based on facial data using the Naive Bayes classification method with the assistance of HOG feature extraction achieved highly satisfying performance. In the study, the model was built using a total of 200 data, where 80% was used as training data and 20% as testing data. The Naive Bayes model was tested with three variations, namely Bernoulli, Multinomial, and Gaussian. Based on the evaluation results, it was found that the Naive Bayes model with the Bernoulli variation achieved an accuracy of 89.72%, which was the highest among the three variations. Meanwhile, the model with the Multinomial variation showed a good performance with an accuracy of 89.47%. However, the model with the Gaussian variation exhibited a lower accuracy of only 65.91%.

Building upon the findings of the previous study[30], the current study explores the use of boosting algorithms for classifying autistic and normal faces based on SURF feature extraction. The results indicate that boosting algorithms, particularly Gradient Boosting, show promising performance in this classification task. With a high accuracy rate of 91.67%, Gradient Boosting outperforms other boosting algorithm variants, including LightGBM and Adaboost. On the other hand, this current study achieved the highest accuracy with the SVM model using HOG feature extraction and RBF, Polynomial, Grid Search, and Random Search kernel functions, with an accuracy of 95% on the 80:20 data split.

The results of this evaluation can be contextualized in the field of facial recognition and data classification, particularly in recognizing autistic and normal data in a specific dataset. The tested classification models in this study can serve as a reference or foundation for further development in facial recognition in medical domains or early detection in educational settings. The use of Surf and Hog feature extractions in combination with SVM in this research demonstrates the potential of these methods in data recognition and classification across various fields.

Despite achieving good performance, this study has some limitations. Firstly, it was conducted on a specific dataset, so generalizing the results to other datasets should be done with caution. Secondly, the study only considered Surf and Hog feature extractions. Exploring other feature extraction methods could reveal their impact on model performance. Lastly, the selection of kernel functions and parameters in SVM was done using Grid Search and Random Search methods, but other techniques like Bayesian Optimization could also be explored to find more optimal parameter combinations.

The recommendation for other researchers is to continue this research in depth, taking into account several important aspects. First, it is recommended to use a more diverse and larger data set so that the model can generalize better. Furthermore, research can be directed towards exploring other feature extraction methods besides HOG and SURF that have been used in this study. In addition, the use of more advanced optimization techniques, such as bayesian optimization or evolutionary optimization techniques, can be explored to perform more efficient tuning of model parameters.

In addition to improvements to the SVM approach, recommendations could also involve the use of deep learning models, such as neural networks. With the advantage of handling complex data and automatically learning feature representations, deep learning models can be a powerful option for solving this classification problem. Experiments can be conducted by building and training deep learning models, such as Convolutional Neural Networks (CNNs) or Transformer models, using the same data set. Furthermore, researchers can compare the performance of deep learning models with the previously investigated SVM approach.

5. Conclusions

This research examines and compares the performance of SVM classification models with HOG and SURF feature extractions on facial data for autism detection. The results of this study show that both HOG and SURF feature extraction methods have good performance in classifying autism data, with consistent accuracy rates in both data division scenarios (70:30 and 80:20). The SVM model with HOG feature extraction achieved an accuracy of 0.95 in the 80:20 data division, while the SVM model with SURF feature extraction achieved an accuracy of 0.9 in the same data division.

This research has benefits in early autism detection based on facial data, which can have a positive impact if used in the selection process of new students in elementary schools. However, there are some limitations in this study, such as limited data which may affect the generalization of the model, and the focus of the research solely on accuracy without considering other metrics such as execution time and model complexity.

As recommendations, future research can enhance the reliability and validity of evaluation results by expanding the amount of data used. Additionally, exploring other feature extraction methods and implementing more advanced deep learning methods can improve the performance of the classification models. By addressing these limitations and implementing the recommendations, further research can make a more significant contribution in the domain of autism detection based on facial data .

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References

[1] C. Zhang, Y. Ma, L. Qiao, L. Zhang, and M. Liu, "Learning to fuse multiple brain functional networks for automated autism identification," *Biology*, vol. 12, no. 7, 2023. [Online]. Available: https://www.mdpi.com/2079-7737/12/7/971

[2] S. L. Hyman, S. E. Levy, S. M. Myers, D. Z. Kuo, S. Apkon, L. F. Davidson, K. A. Ellerbeck, J. E. Foster, G. H. Noritz, M. O. Leppert *et al.*, "Identification, evaluation, and management of children with autism spectrum disorder," *Pediatrics*, vol. 145, no. 1, 2020.

[3] R. Marotta, M. C. Risoleo, G. Messina, L. Parisi, M. Carotenuto, L. Vetri, and M. Roccella, "The neurochemistry of autism," *Brain Sciences*, vol. 10, no. 3, 2020. [Online]. Available: https://www.mdpi.com/2076-3425/10/3/163

[4] M. D. Hossain, H. U. Ahmed, M. Jalal Uddin, W. A. Chowdhury, M. S. Iqbal, R. I. Kabir, I. A. Chowdhury, A. Aftab, P. G. Datta, G. Rabbani *et al.*, "Autism spectrum disorders (asd) in south asia: a systematic review," *BMC psychiatry*, vol. 17, pp. 1–7, 2017.

[5] S. Xie, H. Karlsson, C. Dalman, L. Widman, D. Rai, R. M. Gardner, C. Magnusson, D. E. Schendel, C. J. Newschaffer, and B. K. Lee, "Family history of mental and neurological disorders and risk of autism," *JAMA network open*, vol. 2, no. 3, pp. e190 154–e190 154, 2019.

[6] O. I. Talantseva, R. S. Romanova, E. M. Shurdova, T. A. Dolgorukova, P. S. Sologub, O. S. Titova, D. F. Kleeva, and E. L. Grigorenko, "The global prevalence of autism spectrum disorder: A three-level meta-analysis," *Frontiers in Psychiatry*, vol. 14, p. 1071181, 2023.

[7] M. Bala, M. H. Ali, M. S. Satu, K. F. Hasan, and M. A. Moni, "Efficient machine learning models for early stage detection of autism spectrum disorder," *Algorithms*, vol. 15, no. 5, p. 166, 2022.

[8] I. D. Rodrigues, E. A. de Carvalho, C. P. Santana, and G. S. Bastos, "Machine learning and rs-fmri to identify potential brain regions associated with autism severity," *Algorithms*, vol. 15, no. 6, p. 195, 2022.

[9] S. M. Hasan, M. P. Uddin, M. Al Mamun, M. I. Sharif, A. Ulhaq, and G. Krishnamoorthy, "A machine learning framework for early-stage detection of autism spectrum disorders," *IEEE Access*, vol. 11, pp. 15 038–15 057, 2022.

[10] S. Raj and S. Masood, "Analysis and detection of autism spectrum disorder using machine learning techniques," *Procedia Computer Science*, vol. 167, pp. 994–1004, 2020.

[11] D. Pietrucci, A. Teofani, M. Milanesi, B. Fosso, L. Putignani, F. Messina, G. Pesole, A. Desideri, and G. Chillemi, "Machine learning data analysis highlights the role of parasutterella and alloprevotella in autism spectrum disorders," *Biomedicines*, vol. 10, no. 8, p. 2028, 2022.

[12] S. Cho, M. Liberman, N. Ryant, M. Cola, R. T. Schultz, and J. Parish-Morris, "Automatic detection of autism spectrum disorder in children using acoustic and text features from brief natural conversations." in *Interspeech*, 2019, pp. 2513–2517.

[13] K. S. Omar, P. Mondal, N. S. Khan, M. R. K. Rizvi, and M. N. Islam, "A machine learning approach to predict autism spectrum disorder," in *2019 International conference on electrical, computer and communication engineering (ECCE)*. IEEE, 2019, pp. 1–6.

[14] R. Sujatha, S. Aarthy, J. Chatterjee, A. Alaboudi, and N. Jhanjhi, "A machine learning way to classify autism spectrum disorder," *International Journal of Emerging Technologies in Learning (iJET)*, vol. 16, no. 6, pp. 182–200, 2021.

[15] M. Muhathir, R. Muliono, and M. Hafni, "Image classification of autism spectrum disorder children using naã ve bayes method with hog feature extraction," *Journal of Informatics and Telecommunication Engineering*, vol. 5, no. 2, pp. 494–501, 2022.

[16] P. H. Prastyo, A. S. Sumi, A. W. Dian, and A. E. Permanasari, "Tweets responding to the indonesian government's handling of covid-19: Sentiment analysis using svm with normalized poly kernel," *J. Inf. Syst. Eng. Bus. Intell*, vol. 6, no. 2, p. 112, 2020.

[17] J. Cervantes, F. Garcia-Lamont, L. Rodríguez-Mazahua, and

A. Lopez, "A comprehensive survey on support vector machine classification: Applications, challenges and trends," *Neurocomputing*, vol. 408, pp. 189–215, 2020.

[18] M. Ulfa., R. Syah., and Muhathir., "The classification of tea leaf diseases using sift feature extraction of learning vector quantization method with support vector machine," in *Proceedings of the 3rd International Conference on Advanced Information Scientific Development - ICAISD*, INSTICC. SciTePress, 2024, pp. 10–14.

[19] Z. Gao, S.-C. Fang, X. Gao, J. Luo, and N. Medhin, "A novel kernel-free least squares twin support vector machine for fast and accurate multi-class classification," *Knowledge-Based Systems*, vol. 226, p. 107123, 2021.

[20] V. Piccialli and M. Sciandrone, "Nonlinear optimization and support vector machines," *Annals of Operations Research*, vol. 314, no. 1, pp. 15–47, 2022.

[21] H. Nguyen-Quoc and V. T. Hoang, "A revisit histogram of oriented descriptor for facial color image classification based on fusion of color information," *Journal of Sensors*, vol. 2021, pp. 1–12, 2021.

[22] C. V. B. Murthy, M. L. Shri, S. Kadry, and S. Lim, "Blockchain based cloud computing: Architecture and research challenges," *IEEE Access*, vol. 8, pp. 205 190–205 205, 2020.

[23] M. Melisah and M. Muhathir, "A modification of the distance formula on the k-nearest neighbor method is examined in order to categorize spices from photo using the histogram of oriented gradient," in *2023 International Conference on Computer Science, Information Technology and Engineering (ICCoSITE)*. IEEE, 2023, pp. 23–28.

[24] I. Safira and M. Muhathir, "Analysis of different naïve bayes methods for categorizing spices through photo using the speeded-up robust feature," in *2023 International Conference on Computer Science, Information Technology and Engineering (ICCoSITE)*. IEEE, 2023, pp. 29–34.

[25] A. Vinay, A. R. Deshpande, B. Pranathi, H. Jha, K. B. Murthy, and S. Natarajan, "Effective descriptors based face recognition technique for robotic surveillance systems," *Procedia computer science*, vol. 133, pp. 968–975, 2018.

[26] S. A. K. Tareen and Z. Saleem, "A comparative analysis of sift, surf, kaze, akaze, orb, and brisk," in *2018 International conference on computing, mathematics and engineering technologies (iCoMET)*. IEEE, 2018, pp. 1–10.

[27] M. Muhathir, N. Khairina, R. Karenina, I. Barus, M. Ula, and I. Sahputra, "Preserving cultural heritage through ai: Developing lenet architecture for wayang image classification," *IJACSA) International Journal of Advanced Computer Science and Applications*, vol. 14, no. 9, 2023.

[28] A. Indrawati, A. Rahman, E. Pane *et al.*, "Classification of diseases in oil palm leaves using the googlenet model," *Baghdad Science Journal*, vol. 20, no. 6 (Suppl.), pp. 2508–2508, 2023.

[29] Muhathir, M. F. Dwi Ryandra, R. B. Syah, N. Khairina, and R. Muliono, "Convolutional neural network (cnn) of resnet-50 with inceptionv3 architecture in classification on x-ray image," in *Computer Science On-line Conference*. Springer, 2023, pp. 208–221.

[30] Y. Siagian, Muhathir, and M. D. R, "Classification of autism using feature extraction speed up robust feature (surf) with boosting algorithm," in *2023 International Conference on Information Technology Research and Innovation (ICITRI)*, 2023, pp. 60–64.

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