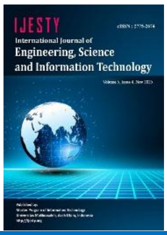
International Journal of Engineering, Science and Information Technology
Volume 5, No. 4 (2025) pp. 152-161
eISSN: 2775-2674
Website: http://ijesty.org/index.php/ijesty
DOI: https://doi.org/10.52088/ijesty.v5i4.1206
Research Paper, Short Communication, Review, Technical Paper



Improving the Classification Performance of SVM, KNN, and Random Forest for Detecting Stress Conditions in Autistic Children

Melinda Melinda[1]*, Yunidar Yunidar[1], Rizka Miftahujjannah[1], Siti Rusdiana[2], Amalia Amalia[3], Lailatul Qadri Zakaria[4]

[1]Department of Electrical and Computer Engineering, Universitas Syiah Kuala, Banda Aceh, Indonesia
[2]Department of Mathematics, Faculty of Mathematics & Natural Sciences, Universitas Syiah Kuala, Banda Aceh, Indonesia
[3]Department of Computer Science, Universitas Sumatera Utara, Medan, Indonesia
[4]Faculty of Information Science and Technology, Universiti Kebangsaan Malaysia, Bangi, Selangor, Malaysia

**Corresponding author Email: melinda@usk.ac.id*

The manuscript was received on 27 February 2025, revised on 15 May 2025, and accepted on 24 August 2025, date of publication 5 November 2025

Abstract

This paper addresses the critical challenges of managing stress in autistic children by introducing an innovative deployable system designed to detect signs of stress through continuous monitoring of physiological and environmental indicators. The system, implemented as a convenient portable detection system, measures key parameters such as heart rate, body temperature and skin conductance. The data is accessed in real-time and displayed on the Blynk application with an IoT system and viewed remotely via an Android device, allowing caregivers to receive instant notifications upon detection of potential stress symptoms. This timely alert system enables rapid intervention, potentially reducing stress intensity and providing peace of mind to caregivers. The study further compares three powerful data analysis methods namely Support Vector Machine (SVM), K-nearest neighbors (KNN) and Random Forest (RF) in interpreting the collected sensor data. The SVM-based system achieved a fairly good detection accuracy of 90%, KNN also showed excellent results of 92% while the Random Forest-based system showed superior performance with an impressive accuracy of 95%. These findings suggest that the Random Forest method exhibits a superior level of effectiveness in accurately predicting the onset of stress conditions., providing the importance for technological advancements that can be applied in supporting better management of autism-related behavioral defenses.

Keywords: *Stress, Blynk, Support Vector Machine, K-nearest neighbors, Random Forest.*

1. Introduction

Stress can easily arise during childhood and adolescence. Young people facing tough situations, like losing a parent, experiencing family divorce, or dealing with bullying, often struggle with their mental health [1]. The impact of stress can extend beyond emotions, influencing both psychological and physical well-being [2]. It may interfere with growth, metabolism, reproductive health, and immune function. Moreover, stress can lead to changes in behavior. Children with autism, for instance, can also feel the effects of stress in their daily lives [3]. Autism is marked by challenges in verbal and non-verbal communication, along with repeated movements [4]. This study revealed that autism tends to be diagnosed more often in male individuals than female individuals [5].

Recent developments have resulted in systems designed to detect early signs of stress through the monitoring of physiological responses and environmental sound analysis [5]. For example, stress detection systems that include factors such as blood pressure, heart rate, and body temperature have shown potential [6]. This paper presents an innovative portable system detection created to identify preliminary stress indicators in children with autism by integrating sensors that track heart rate, body temperature, skin conductance, and surrounding noise levels [7]. The system utilizes Internet of Things (IoT) technology to offer real-time data accessibility through a smartphone app, which enhances the ability of caregivers to respond quickly [8]. Machine Learning (ML), a branch of artificial intelligence, enables a system to learn patterns from data and gradually improve its performance over time without requiring explicit programming [9-10]. This capability is especially useful in classifying and predicting complex patterns, such as those associated with Autism Spectrum Disorder (ASD) [11]. Recent studies have investigated various ML methodologies to enhance the precision and effectiveness of ASD diagnostics. For example, Alfita Khairah et al. [12] employed a diverse range of ML algorithms, achieving prediction accuracies of 94% with

Logistic Regression (LR) . Likewise, Stewart et al. [13] devised an algorithm to assess the urgency of mental health services for children with ASD, using decision tree models to effectively recognize and prioritize service requirements.
In a separate study [14] The results of this study also indicate that the use of wearable technology has proven to be feasible and effective in detecting stress. The developed stress classification model achieved an accuracy rate of 92% and demonstrated a significant correlation between physiological parameters and directly observable symptoms. Responses from caregivers reinforced these findings, with 85% of respondents stating that the device helped them manage stress-causing stimuli and tantrum behavior. However, several challenges remained, particularly regarding the device's adhesion and comfort when used by younger children, necessitating further development to improve the device's durability and comfort, Pergantis et al. [15] Applying nested cross-validation to 76 sample periods (consisting of 38 rest periods and 38 stress periods), LR and SVM algorithms were trained and evaluated to classify each validation sample into the rest or stress category. The evaluation results showed that the SVM model achieved 93% accuracy, while the LR model achieved 87% accuracy. While the system effectively showcased its capabilities in a controlled setting, the testing was restricted to neurotypical children and did not involve classification or comparative analysis [16]. The employment of fuzzy logic in this research presents various limitations that warrant consideration. Firstly, the complexity of design poses a challenge, as the formulation of suitable fuzzy rules and membership functions necessitates comprehensive knowledge of the analyzed system. Moreover, the accuracy of outcomes is heavily influenced by the quality and selection of input parameters; inaccuracies in the input data will also compromise the results obtained [16]. Conversely, the current research expands upon this foundation by applying the identical sensor-based system to children with ASD and integrating machine learning classifiers such as SVM, KNN ,and RF to identify early stress signals in children with ASD. This study presents an innovative method by specifically targeting tantrum behavior, a prevalent but often overlooked facet of ASD.
The objectives of this study are as follows:

1. To develop a comprehensive classification system for detecting stress conditions in autistic children using physiological data such as heart rate, body temperature, and skin conductance.
2. To improve the classification performance by comparing and evaluating the effectiveness of SVM, KNN, and RF algorithms in accurately identifying early signs of stress or normal conditions.

This study utilized learning algorithms, including SVM, KNN, and RF, to maximize the effectiveness of each approach in classifying tantrums. In this study, the performance of the three methods was analyzed using evaluation metrics, including precision, recall, F1-score, and accuracy, to identify the most optimal algorithm for detecting tantrums. Furthermore, this study also discussed the potential of real-time physiological monitoring to support rapid and appropriate interventions, which in turn could improve the quality of life for children with ASD and their families..

2. Literature Review

Literature that describes the main stages in Stress, SVM Classification, KNN, Random Forest and Confusion Matrix as explained below:

2.1. Stress

According to the American Psychological Association, stress can be classified into three main categories, namely acute stress, acute episodic stress, and chronic stress. [16]. Stress can lead to a range of health problems, such as hypertension and headaches [13]. During pregnancy, stress may affect fetal brain development and elevate the risk of autism [17]. Children diagnosed with autism may experience seizures and have self-harming behaviors due to increased anxiety [18]. Stress causes physiological changes, including variations in heart rate, body temperature, and skin conductance [8], [11]. Tables 1 and 2 illustrate the distinctions between typical children and those with autism. Typical children generally maintain a heart rate between 60-100 BPM, a body temperature of 36-37ºC, and a skin conductance of 2-4 µS, whereas children with autism frequently display a heart rate of 70-110 BPM, a body temperature of 37-38ºC, and a skin conductance of 1-3 [18].

Table 1. Changes Parameters in Normal Children

Condition	Heart Rate (BPM)	Body temperature (ºC)	Skin Conductance (µS)
Normal	60-100	36-37	2-4
Stress	100-120	32-36	4-6

Table 2. Changes Parameters in Children with Autism

Condition	Heart Rate (BPM)	Body temperature (ºC)	Skin Conductance (µS)
Normal	70-110	37-38	1-3
Stress	110-130	33-37	3-5

2.2. Support Vector Machine (SVM)

SVM is a supervised machine learning technique widely used in various classification and regression problems [19]. In the context of classification, SVM work by finding an optimal separating hyperplane that can distinguish data into two different classes with the maximum separation distance or margin. This margin is defined as the shortest distance between the hyperplane and data points from each class, known as support vectors. By maximizing the interclass margin, SVM aims to improve the model's ability to generalize to new, previously unseen data, thereby minimizing the risk of overfitting [19]. SVMs work by finding the optimal hyperplane that maximizes the separation margin between classes, thereby improving generalization and reducing the risk of overfitting. Kernel functions enable SVMs to handle non-linearly distributed data by transforming it into higher-dimensional spaces. Previous literature has extensively discussed the theoretical power and applications of SVMs in areas such as EEG signal processing and medical diagnosis. However, there is limited research directly applying SVMs to detect real-time stress in autistic children, particularly by incorporating multiple physiological parameters. This study extends this approach with a practical implementation and performance evaluation of SVMs in this context. One of the main advantages of SVM is its ability to efficiently solve binary subscripts, especially when the data is not linearly separable. In such situations, SVM uses a kernel function to transform the original feature space into a higher-dimensional space, thus enabling the search for an optimal separating hyperplane. This kernel function has various variants, including linear, polynomial, radial basis function (RBF), and sigmoid kernels, the selection of which is adjusted to the data distribution pattern being analyzed. Although SVM is primarily designed for two-class classification, this algorithm can be adapted to handle multiclass classification problems through strategies such as one-vs-one or one-vs-all. This makes SVM a flexible method and is widely applied in various fields, including pattern recognition, bioinformatics, EEG signal processing, and data-driven diagnostic systems. With a robust mathematical approach and good performance on high-dimensional data and a limited number of samples, SVM remains one of the popular algorithms in the development of modern classification systems [20].

2.3. K-nearest neighbors (KNN)

KNN is one of the most frequently used supervised machine learning algorithms in classification tasks, although it also has applications in regression problems [21]. KNN works by measuring the distance between test data and a number of its nearest neighbors in the training dataset. Despite its simplicity and non-parametric nature, selecting the right k value significantly determines model performance. The literature often cites KNN's advantages in terms of interpretability and flexibility to complex data distributions. However, limitations such as computational inefficiency on large datasets and sensitivity to irrelevant features remain challenges. This study re-evaluates the effectiveness of KNN in a controlled scenario with limited but structured physiological data, providing new insights into its application in wearable-based stress detection systems. In the context of classification, this algorithm determines the class of a test dataset based on the majority class of its k nearest neighbors. In regression, predictions are made by calculating the average value of these neighbors. Therefore, selecting the correct k value has a significant impact on model performance and accuracy. KNN advantages lies in its non-parametric nature it does not assume a specific distribution for the data being analyzed. This makes KNN highly flexible for use on data with complex or previously unknown distribution characteristics. Furthermore, KNN is also categorized as an instance-based learning method because the prediction process is performed by directly referring to stored data instances, rather than through a parameter learning process, as in other predictive models. KNN is often categorized as a lazy learner or passive learner algorithm because it does not carry out an explicit training process during the training phase. Instead of actively building a predictive model, KNN stores all training data and only performs distance calculations and decision-making during the classification process [22]. This approach has the advantages of simplicity and interpretability. Still, it can also be computationally inefficient, especially when faced with large datasets, because the entire training data must be accessed each time a prediction is made.

2.4. Random Forest (RF)

RF is an ensemble learning technique widely used in classification and regression tasks. This algorithm works by simultaneously building multiple decision trees during the training process. This method improves accuracy and generalizability by reducing variance through random feature selection and a voting mechanism. The literature confirms RF robustness to noise and data continuity, making it a popular method in biomedical applications. Despite its frequent use, there are few studies comprehensively comparing RF with other models in real-time stress classification in children with ASD. This study fills this gap by providing empirical evidence of RF superior performance in this setting [23]. The final prediction is then determined based on the mode (majority class) of all trees for classification tasks, or the mean value for regression tasks [23][24]. This approach aims to improve prediction accuracy and stability by combining the strengths of many weak learners into a single, stronger model (strong learner). The process of building a Random Forest begins with the creation of several bootstrap samples from the original dataset. This bootstrap technique involves random sampling with replacement until a new dataset is formed. Typically, the RF algorithm generates hundreds of trees, and in everyday practice, around 500 trees are used to achieve stable results [25]. Interestingly, because the sampling technique uses replacement, approximately 63% of the original data will appear at least once in each bootstrap sample. In contrast, the remaining unsampled data is referred to as out-of-bag (OOB) data [26]. This OOB data is beneficial because it can be used to evaluate model performance without requiring separate validation data. Each bootstrap sample is used to build a single decision tree, and during the tree formation process, only a small subset of features is randomly selected for each split at the tree node. This strategy helps reduce correlation between trees and promotes diversity within the ensemble, ultimately improving the model's generalizability to new data [27].

2.5. Confusion Matrix

The confusion matrix is a standard evaluation tool in classification models are evaluated by constructing the confusion matrix for test data [28]. In addition, accuracy, sensitivity, and specificity are also measured for each model. The definitions for these matrices are as follows :

$$recall = \frac{TP}{TP+FN} \tag{1}$$

$$precision = \frac{TP}{TP+FP} \tag{2}$$

$$accuracy = \frac{TP+TN}{TP+FN+FP+TN} \tag{3}$$

$$F1 = 2. = \frac{Precision\ x\ Recall}{Precision+\ Recall} \tag{4}$$

TP, TN, FP, and FN are True Positive (correctly predicted positive), True Negative (correctly predicted negative), False Positive (incorrectly predicted positive), and False Negative (incorrectly predicted negative) [29].

3. Methods

The collected data was then classified using SVM, KNN, and RF algorithms. The performance of these models was evaluated using a confusion matrix, with key metrics including precision, recall, accuracy, and F1-score to determine the effectiveness of the system in accurately identifying tantrum signals.

3.1. Dataset

This study uses a dataset taken from a previous study conducted by Melinda et al. [16]. In this study, researchers designed and implemented a fuzzy logic and Internet of Things (IoT)-based stress detection system specifically for children with autism spectrum disorder. This system utilizes three primary physiological parameters: heart rate, body temperature, and skin conductance, which are measured using the MAX30100, DS18B20, and GSR sensors, respectively. Data collection was carried out at the My Hope Special Needs Center Foundation in Banda Aceh, involving five children with autism, consisting of three boys and two girls aged between 5 and 9 years. Each subject was tested 20 times at varying times between 15 and 30 minutes, resulting in a total of 100 physiological data samples collected. Each sample contained information on heart rate measurements, body temperature, and skin conductance.

Through the fuzzy logic system designed in this study, each data set was classified into two conditions: normal and stressed, based on 64 fuzzy rules that combined the values of the three physiological parameters. Based on the classification results, 54 data sets were categorized as stressed, while the remaining 46 were classified as normal. The range of values for stressed conditions, based on fuzzy calculations, ranged from 52.99% to 75%, while the range for normal conditions ranged from 25% to 46.89% of the total detection scale. This classified dataset was then utilized in our current study to conduct further analysis using machine learning-based classification methods, including SVM, KNN and RF. The goal was to illuminate and compare the performance of these three methods in classifying stressed and normal conditions in autistic children based on the same physiological parameters [16].

3.2. Support Vector Machine (SVM)

The workflow of a child stress detection system using the SVM method is presented in a flowchart that depicts the main stages of the classification process based on children's physiological data. This diagram serves as a conceptual framework for explaining how physiological data, such as heart rate, body temperature, and skin conductance[16] are processed to identify stress conditions early. For more details, see Figure 1 below.

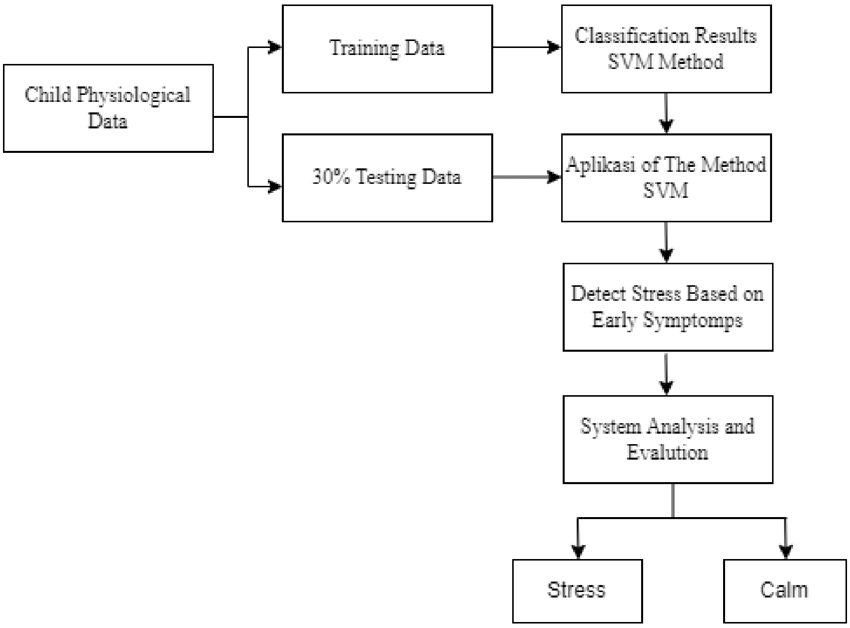


Fig 1. Classification Process Using SVM Method

Based on Figure 1, the process begins with the collection of the child's physiological data, which is then divided into two parts 70% is used as training data, and 30% as testing data. Training data is used to train the model using the SVM method for classification. After the SVM model is trained, testing is performed on 30% of the unknown data to evaluate the model's performance. The SVM model is then applied to detect stress based on the initial symptoms that appear in the child's physiological data. The classification results will indicate whether the child's condition falls into the stress or calm category. After that, a system analysis and evaluation of the classification results are carried out to ensure the accuracy and effectiveness of the model built.

3.3. K-nearest neighbors (KNN)

The following stages systematically describe the process of classifying stress conditions in children based on physiological data, using the KNN method as the main algorithm. The following figure presents a flowchart that summarizes the workflow of a stress detection system using this approach. The process begins with collecting the child's physiological data, which includes various parameters, the data of which are taken based on research [16]. The following flowchart of the KNN classification is shown in Figure 2.

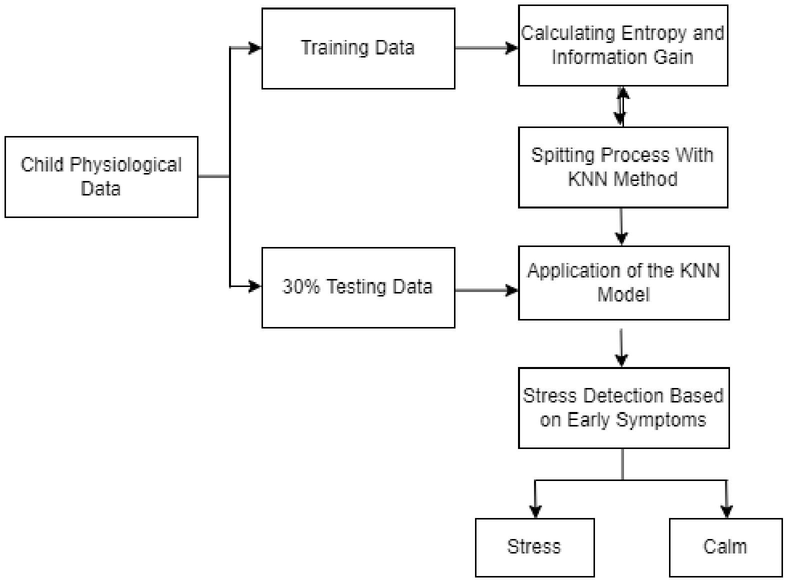


Fig 2. Classification Process Using KNN Method

The Figure 2 above illustrates the process flow for classifying stress in children based on physiological data using the KNN method. The process begins with collecting the child's physiological data, which is then divided into two parts: training data and testing data, with 30% of the data used for testing. During the training phase, entropy and information gain calculations are performed to evaluate the level of uncertainty and attribute contribution to the classification. Next, the data is processed using the KNN method, which calculates the proximity between the test data and several nearest neighbors in the training data. The KNN model is then applied to detect stress based on initial symptoms identified from the input data. The final result of this process is the classification of the child's condition into two categories: stressed or calm. This flow demonstrates a systematic approach to analyzing physiological data to detect potential stress in children more accurately and earlier.

3.4. Random Forest (RF)

The following figure shows a flowchart of the process of classifying stress conditions in children using the RF method. This diagram is designed to comprehensively illustrate the systematic steps implemented in the study. It begins with initial data in the form of the child's physiological information, such as heart rate, body temperature, and skin conductance, based on research [16]. The data is then processed and divided into two parts: training data and testing data. For more details, see Figure 3.

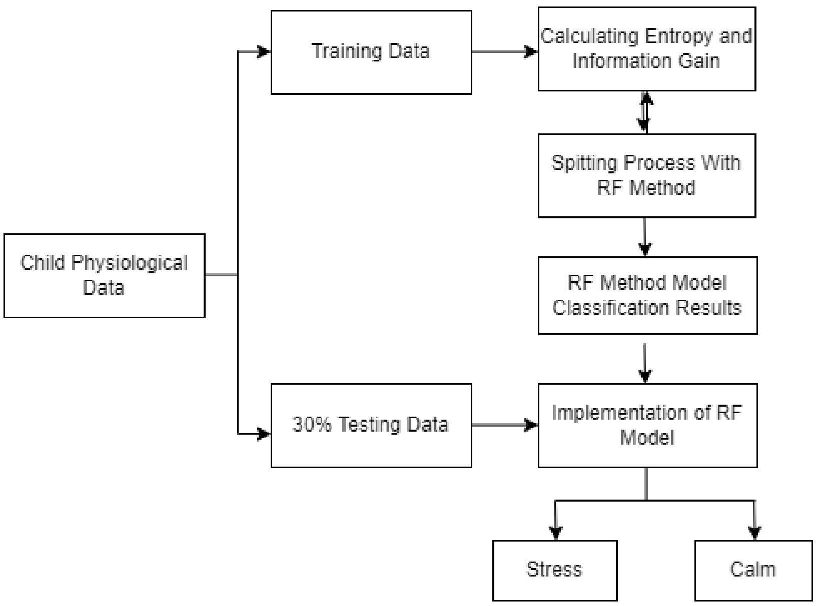


Fig. 3 Classification Process Using RF Method

In Figure 3, data is categorized using the Random Forest (RF) approach. RF creates a diagram resembling a tree structure with roots, branches, and leaves. The root features a set of data attributes, branches contain decision-making rules and outputs from the results of the splitting tests, while leaves represent class labels or final decisions. The classification process utilizes physiological data from the child's test results with the system. The outcome of the RF classification process separates the data into two categories: tantrum and calm.

4. Result and Discussion

4.1. Classification using SVM

At this stage, the data classification of stress detector measurement results in autistic children is carried out from the aspects of Heart Rate (BPM), Body Temperature (°C) and Skin Conductance (µS) using the SVM classification method. Testing was carried out on 5 autistic children, each child was measured 20 times, so a total of 100 sets of physiological data were used in the analysis and testing of the stress detection system. Data classification using this method is carried out based on the stages described in Figure 3, so that by using the confusion matrix, the accuracy of the classification test obtained using the SVM method can be measured. The results of the performance accuracy analysis can be seen in Figure 4.

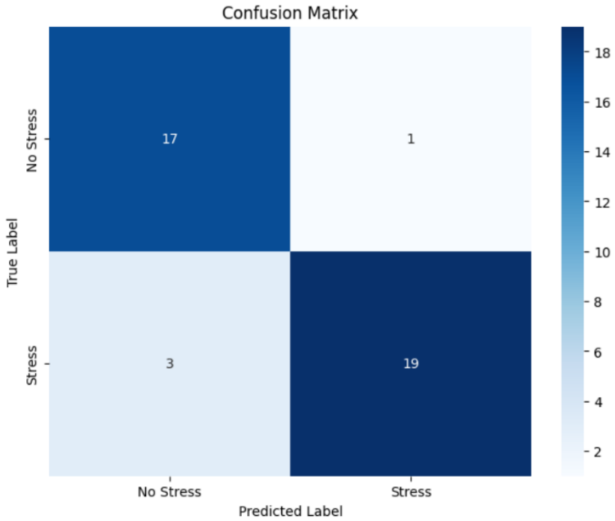


Fig 4. SVM accuracy results using the confusion matrix

Based on Figure 4, it can be seen that there are 17 data categorized as False Negative (FN), 1 data categorized as False Positive (FP), 19 data categorized as True Positive (TP), and 3 data categorized as True Negative (TN). From the 4 quadrant data, the accuracy value of the SVM method is obtained as in Table 3.

Table 3. SVM Method Classification Accuracy Results

Precision	Recall	F1-Score	Accuracy
95%	86.36%	90.48%	90%

Based on Table 3, the classification performance using the SVM method showed very satisfactory results in detecting stress in children. This model achieved an accuracy rate of 90.00%, meaning that out of every 100 cases, 90 were correctly classified. The high precision value of 95.00% indicates that most optimistic predictions (children experiencing stress) were indeed accurate, making the possibility of false positive prediction errors minimal. Meanwhile, the recall value of 86.36% indicates that the model is quite effective in recognizing most stress cases, although some cases are still not detected (false negatives). With an F1-score of 90.48%, the SVM model strikes a good balance between accurately and comprehensively identifying stress cases. Overall, these results confirm that SVM is an effective and reliable method for stress classification systems based on children's physiological data.

4.2. Classification using KNN

At this stage, the classification process of the stress detection data collected from autistic children is performed by analyzing three physiological parameters: Heart Rate (BPM), Body Temperature (°C), and Skin Conductance (µS). The classification employs the KNN algorithm to determine the stress levels. Measurements were conducted on 5 autistic children, with each child undergoing 20 sessions, resulting in a total of 100 physiological data samples. The classification workflow adheres to the procedure outlined in Figure 2, which includes preprocessing, feature analysis, and application of the KNN method. To evaluate the system's performance, a confusion matrix was used, allowing for a detailed assessment of classification results. To assess system performance, a confusion matrix is used to provide a detailed overview of the classification results. A visualization of the performance evaluation results using the KNN classification algorithm is shown in Figure 5.

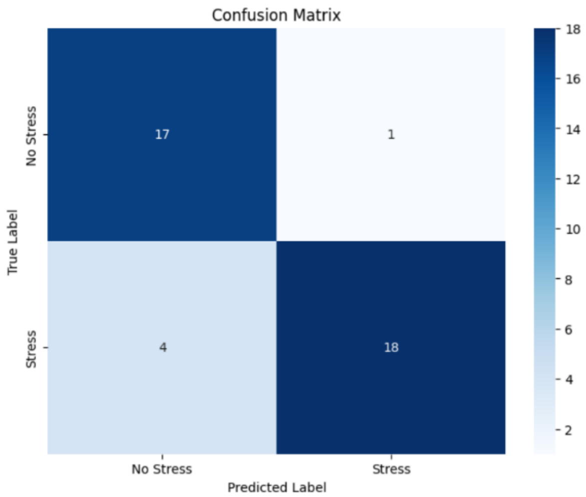


Fig 5. KNN accuracy results using the confusion matrix

Based on Figure 5, it can be seen that there are 17 data categorized as False Negative (FN), 1 data categorized as False Positive (FP), 18 data categorized as True Positive (TP), and 4 data categorized as True Negative (TN). From the 4 quadrant data, the accuracy value of the KNN method is obtained as in Table 4.

Table 4. KNN Method Classification Accuracy Results

Precision	Recall	F1-Score	Accuracy
95%	95.45%	93.33%	92.50%

Can be seen in Table 4, the classification results using the KNN method showed excellent performance in detecting stress in autistic children. A precision of 95% and a recall of 95.45% indicate that the model accurately and comprehensively identifies stress conditions. The F1-score of 93.33% reflects the balance between precision and sensitivity, while the overall accuracy reaches 92.50%. With these results, KNN is proven to be effective for stress classification based on children's physiological data.

4.3. Classification using RF

The classification process using RF begins with dividing the physiological data, with 70% used for training and the remaining 30% for testing. During the training phase, several decision trees are generated, each of which is drilled using a random subset of the training data through bootstrap sampling. During the branch formation process within each tree, features are randomly selected to ensure diversity between trees and minimize the potential for overfitting. Each tree classifies the testing data on its own, and the overall classification is decided by majority voting from all the trees. In contrast to a single decision tree, which uses all features and training data to create one tree, the random forest's approach of employing multiple trees with random feature selection enhances its robustness and diminishes the likelihood of overfitting, leading to more precise predictions. At this point, the classification of the measurement results from the early tantrum symptom detector is performed using the random forest classification technique. The classification utilizes 100 data points from 5 children, consisting of 54 data points under stress conditions and 46 data points in normal conditions. The outcome of the performance analysis using the RF classifier is presented in Figure 6.

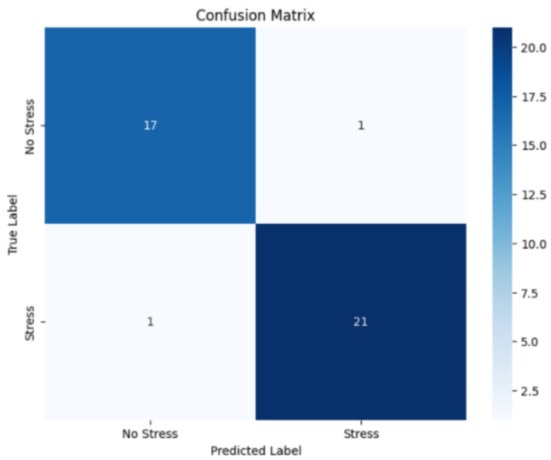


Fig 6. RF accuracy results using the confusion matrix

Based on Figure 6, it can be seen that there are 1 data categorized as False Negative (FN), 1 data categorized as False Positive (FP), 21 data categorized as True Positive (TP), and 17 data categorized as True Negative (TN). From the 4 quadrant data, the accuracy value of the RF method is obtained as in Table 5.

Table 5. RF Method Classification Accuracy Results

Precision	Recall	F1-Score	Accuracy
96%	96%	98%	95%

Based on Table 5, the classification results using the Random Forest (RF) method show very good performance. Precision and recall of 96% each indicate that the model is very accurate and reliable in detecting stress conditions. The high F1-score of 98% reflects the optimal balance between precision and sensitivity. With an overall accuracy of 95%, the RF method has proven effective for stress classification based on physiological data of autistic children.

4.4. Comparison Classification SVM,KNN and RF

In this study, three classification methods SVM, KNN, and RF were compared to detect stress in children with ASD based on physiological data, including heart rate, body temperature, and skin conductance. The evaluation results showed that all three methods performed well, although with varying degrees of effectiveness. The SVM method achieved 90% accuracy, indicating that the model is quite reliable in classification. However, despite its high precision, the lower recall rate demonstrates that the SVM still misses some stress cases that should have been detected. The KNN method achieved 92.5% accuracy, striking a balance between precision and sensitivity in identifying stress conditions. This indicates improved performance in terms of correct case detection compared to the SVM. The most significant improvement was achieved by the Random Forest method, which achieved the highest accuracy of 95%. The main advantage of the RF method lies in its ability to combine multiple decision trees through an ensemble learning approach, thus recognizing complex patterns in the data and effectively minimizing classification errors. Furthermore, RF is known to be more robust to data noise and imbalanced data distribution, making it the most reliable method in this stress detection system.

This study successfully demonstrated a significant improvement in classification performance when using the Random Forest approach compared to the SVM and KNN methods. The application of RF not only provided the highest accuracy but also provided greater stability and efficiency in distinguishing between stress and normal conditions in autistic children. These results indicate that developing and improving machine learning-based classification models, particularly through the integration of the Random Forest method, can significantly enhance the accuracy of real-time physiological data-based stress detection systems..

Comparison of various studies related to this study, each using different models and techniques. Based on study [16] Previous study using Fuzzy Logic successfully detected stress and normal conditions in 5 autistic children, utilizing 100 measurement data points and 64 rules based on three physiological parameters. Although this system was able to distinguish between body conditions with a stress percentage range of 52.99%–75% and normal conditions with a range of 25%–46.89%, quantitative evaluations such as accuracy or F1-score were not provided, making its performance difficult to measure objectively. For comparison, this study employed SVM, KNN, and Random Forest algorithms, evaluated using a confusion matrix, with results indicating superior statistical performance. Among the three, Random Forest showed the most optimal results with an accuracy of 95% and an F1-score of 98%, making it the most effective method for stress classification based on physiological data. Meanwhile, another study [30] divided stress levels into three categories—highly stressed, moderately stressed, and not stressed—by first preprocessing the survey data. Various algorithms, including decision trees, random forests, AdaBoost, gradient boosting, and other ensemble approaches, were employed to handle the minority class. An oversampling technique was employed to address the dataset's imbalance. Model evaluation was conducted using several metrics, including the confusion matrix, accuracy, precision, recall, and F1-score. The results of this study demonstrated that an effective ensemble learning model for academic stress classification achieved an F1-score of 93.14% and an accuracy of 93.48%. Five-fold cross-validation also showed consistent performance with an accuracy of 93.45%. Based on several comparisons in previous studies, it can be stated that the random forest method's accuracy in predicting stress in autistic children is very high, at 95%. This indicates that the study is highly promising compared to previous studies, as its accuracy level is exceptionally high. Although the developed device demonstrates accurate and accessible results in real-time, the sample size used in the testing remains limited, comprising only five autistic children and a total of 100 measurement data points. This limitation can increase the risk of overfitting if the data is used to train further machine learning models. Therefore, additional research is recommended, covering a wider range of subjects and with a larger dataset, to ensure the model's generalizability and system specifications across a more representative population. Considering the evaluation results outlined above, the objectives of this research were clearly and measurably formulated from the outset and consistently addressed through the discussion of the classification results. This reflects a strong coherence between the formulation of objectives, methods, and analysis of findings within the overall study structure.

5. Conclusion

This study demonstrates a strong coherence between the stated objectives and the achieved results. The objectives have been explicitly formulated and are measurable, and they have been consistently analyzed throughout the discussion, thereby strengthening the logical structure and scientific integrity of the entire study. This study shows the effectiveness of the SVM, KNN, and RF machine learning methods in classifying stress conditions in autistic children based on physiological parameters, including heart rate, body temperature, and skin conductance. The data used consisted of 100 measurement samples obtained from 5 autistic children, each of whom was measured 20 times. Of the total data, 54 showed stress conditions, and 46 showed normal conditions. Among the three methods tested, Random Forest showed the best performance with an accuracy of 95%, precision and recall of 96%, and an F1-score of 98%. These results show the reliability and accuracy of RF in detecting stress. The KNN method followed with an accuracy of 92.5%, while SVM had the lowest accuracy of 90%. When compared to the previous approach using Fuzzy Logic, which relies on 64 manual rules and does not have a quantitative evaluation, the machine learning method, especially RF, proved to be more accurate, adaptive, and scalable. Therefore, Random Forest is the most appropriate method for an intelligent and real-time stress detection system for children with autism. Although the results are promising, several significant limitations should be noted. First, the data used is still limited, with only 100 samples from five participants, so the model's generalizability to the broader population cannot be guaranteed. Second, the physiological parameters used are limited to three types, which may not fully represent the complexity of the stress response of autistic children. Third, testing was conducted in limited laboratory conditions, so the system's effectiveness under real-world or dynamic conditions has not been thoroughly tested. For future development, it is recommended to increase the number and diversity of subjects to strengthen the model's external validity. The addition of parameters such as respiratory rate, facial expression, or heart rate variability could provide a more comprehensive picture of stress conditions. Furthermore, the real-time implementation of the system through edge computing-based wearable devices, combined with the integration of adaptive learning to adjust to individual stress thresholds, could enhance the accuracy and personalization of continuous stress monitoring. Further longitudinal research is also needed to test the system's long-term robustness and reliability.

Acknowledgement

This research is financially supported by Universitas Syiah Kuala, Ministry of Education, Culture, Research, and Technology of the Republic of Indonesia, in accordance with the Research Assignment Agreement Contract for Associate Lecturer for the 2022 Fiscal Year (Contract Number: 145/UN11/SPK/PNBP/2022) dated February 11, 2022. We would like to thank Universitas Syiah Kuala and all parties who have supported this study.

References

[1] M. Mousikou, A. Kyriakou, and N. Skordis, "Stress and growth in children and adolescents," *Hormone Research in Paediatrics*, vol. 96, no. 1, pp. 25–33, Mar. 2023, doi: 10.1159/000521074.

[2] V. Codazzi, G. Frontino, L. Galimberti, *et al.*, "Mechanisms and risk factors of metabolic syndrome in children and adolescents," *Endocrine*, vol. 84, pp. 16–28, 2024, doi: 10.1007/s12020-023-03642-x.

[3] T. Yalim and S. Mohamed, "Meltdown in Autism: Challenges and Support Needed for Parents of Children with Autism," Int. J. Acad. Res. Progress. Educ. Dev., vol. 12, no. 1, 2023, doi: 10.6007/ijarped/v12-i1/16184.

[4] I. Y. Afif et al., "Effect of Short-Term Deep-Pressure Portable Seat on Behavioral and Biological Stress in Children with Autism Spectrum Disorders: A Pilot Study," Bioengineering, vol. 9, no. 2, 2022, doi: 10.3390/bioengineering9020048

[5] M. Lotan and M. Icht, "Diagnosing Pain in Individuals with Intellectual and Developmental Disabilities: Current State and Novel Technological Solutions," Diagnostics, vol. 13, no. 3, 2023, doi: 10.3390/diagnostics13030401.

[6] G. Ribeiro, O. Postolache and F. F. Martín, "A New Intelligent Approach for Automatic Stress Level Assessment Based on Multiple Physiological Parameters Monitoring," in *IEEE Transactions on Instrumentation and Measurement*, vol. 73, pp. 1-14, 2024, Art no. 4001714, doi: 10.1109/TIM.2023.3342218

[7] C. B. D. Kuncoro, A. Efendi, W.-J. Luo, M. M. Sakanti, and M. I. Ammarullah, "Wireless-based portable device heart rate measurement as biomedical devices for stress detection," *AIP Advances*, vol. 14, no. 4, p. 045021, Apr. 2024, doi: 10.1063/5.0200619.

[8] H. E. Semary, K. A. Al-Karawi, M. M. Abdelwahab, and A. M. Elshabrawy, "A Review on Internet of Things (IoT)-Related Disabilities and Their Implications," J. Disabil. Res., vol. 3, no. 2, pp. 1–16, 2024, doi: 10.57197/jdr-2024-0012.

[9] O. J. Adeyeye and I. Akanbi, "Artificial intelligence for systems engineering complexity: a review on the use of AI and machine learning algorithms," *Computer Science & IT Research Journal*, vol. 5, no. 4, pp. 787–808, 2024, doi: 10.51594/csitrj.v5i4.1026.

[10] M. M. Taye, "Understanding of machine learning with deep learning: Architectures, workflow, applications and future directions," *Computers*, vol. 12, no. 5, p. 91, 2023, doi: 10.3390/computers12050091.

[11] A. K. Rehn, V. R. Caruso, and S. Kumar, "The effectiveness of animal-assisted therapy for children and adolescents with autism spectrum disorder: A systematic review," *Complementary Therapies in Clinical Practice*, vol. 50, p. 101719, 2023, doi: 10.1016/j.ctcp.2022.101719.

[12] A. Khairah, Melinda, I. Hasanuddin, D. Asmadi, R. Arifin, and R. Miftahujjannah, "University students stress detection during final report subject by using NASA TLX method and logistic regression," *Jurnal RESTI (Rekayasa Sistem dan Teknologi Informasi)*, vol. 9, no. 3, pp. 215–226, 2025, doi: 10.29207/resti.v9i3.6401.

[13] S. L. Stewart, G. K.C. King, J. N. Van Dyke, and J. W. Poss, "Predicting Service Urgency in Children and Youth with Autism Spectrum Disorder: The Development of an Algorithm," J. Psychiatry Psychiatr. Disord., vol. 07, no. 06, pp. 210–222, 2023, doi: 10.26502/jppd.2572-519x0202.

[14] R. Rahman, M. Samiun, N. Mohammad, M. Prabha, A. M. Zaman, R. Khan, and M. Hossain, "Wearable technology for real-time monitoring of stress and behavior in autistic individuals in the USA," *Journal of Management*, vol. 2, pp. 70–77, 2025, doi: 10.53935/jomw.v2024i4.869.

[15] P. Pergantis, V. Bamicha, A. Doulou, A. I. Christou, N. Bardis, C. Skianis, and A. Drigas, "Assistive and emerging technologies to detect and reduce neurophysiological stress and anxiety in children and adolescents with autism and sensory processing disorders: A systematic review," *Technologies*, vol. 13, no. 4, p. 144, 2025, doi: 10.3390/technologies13040144.

[16] M. Melinda, V. Setiawan, Y. Yunidar, G. Sakarkar, and N. Basir, "Portable stress detection system for autistic children using fuzzy logic," *Jurnal Nasional Teknik Elektro*, vol. 13, no. 2, pp. 61–68, Jul. 2024, doi: 10.25077/jnte.v13n2.1203.2024.

[17] C. Love, L. Sominsky, M. O'Hely, *et al.*, "Prenatal environmental risk factors for autism spectrum disorder and their potential mechanisms," *BMC Medicine*, vol. 22, p. 393, 2024, doi: 10.1186/s12916-024-03617-3.

[18] A. Frolli, G. Savarese, F. Di Carmine, A. Bosco, E. Saviano, A. Rega, M. Carotenuto, and M. C. Ricci, "Children on the autism spectrum and the use of virtual reality for supporting social skills," *Children*, vol. 9, no. 2, p. 181, 2022, doi: 10.3390/children9020181.

[19] A. Roy and S. Chakraborty, "Support vector machine in structural reliability analysis: A review," *Reliability Engineering & System Safety*, vol. 233, p. 109126, 2023, doi: 10.1016/j.ress.2023.109126.

[20] I. Malashin, V. Tynchenko, A. Gantimurov, V. Nelyub, and A. Borodulin, "Support vector machines in polymer science: A review," *Polymers*, vol. 17, no. 4, p. 491, 2025, doi: 10.3390/polym17040491.

[21] H. Li, "K-nearest neighbor," in *Machine Learning Methods*, Singapore: Springer, 2024, doi: 10.1007/978-981-99-3917-6_3.

[22] R. K. Halder, M. N. Uddin, M. A. Uddin, *et al.*, "Enhancing K-nearest neighbor algorithm: a comprehensive review and performance analysis of modifications," *Journal of Big Data*, vol. 11, p. 113, 2024, doi: 10.1186/s40537-024-00973-y.

[23] H. A. Salman, A. Kalakech, and A. Steiti, "Random forest algorithm overview," *Babylonian Journal of Machine Learning*, pp. 69–79, 2024, doi: 10.58496/BJML/2024/007.

[24] Z. Sun, G. Wang, P. Li, H. Wang, M. Zhang, and X. Liang, “An improved random forest based on the classification accuracy and correlation measurement of decision trees,” *Expert Systems with Applications*, vol. 237, p. 121549, 2024, doi: 10.1016/j.eswa.2023.121549.

[25] N. Jalal, A. Mehmood, G. S. Choi, and I. Ashraf, “A novel improved random forest for text classification using feature ranking and optimal number of trees,” *Journal of King Saud University - Computer and Information Sciences*, vol. 34, no. 6, pp. 2733–2742, 2022, doi: 10.1016/j.jksuci.2022.03.012.

[26] C. Avcı, M. Budak, N. Yağmur, and F. Balçık, “Comparison between random forest and support vector machine algorithms for LULC classification”, IJEG, vol. 8, no. 1, pp. 1–10, 2023, doi: 10.26833/ijeg.987605.

[27] J. Kim, D. Yoon and H. -s. Kim, "Random Forest Approach in Prediction Workers' Stress from Personality Traits," *2022 13th International Conference on Information and Communication Technology Convergence (ICTC)*, Jeju Island, Korea, Republic of, 2022, pp. 2356-2358, doi: 10.1109/ICTC55196.2022.9952879.

[28] K. Takahashi, K. Yamamoto, A. Kuchiba, et al., "Confidence interval for micro-averaged F1 and macro-averaged F1 scores,"Applied Intelligence, vol. 52, pp. 4961–4972, 2022. doi: 10.1007/s10489-021-02635-5.

[29] M. Lotan and M. Icht, “Diagnosing Pain in Individuals with Intellectual and Developmental Disabilities: Current State and Novel Technological Solutions,” Diagnostics, vol. 13, no. 3, 2023, doi: 10.3390/diagnostics13030401. S. Mukodimah and C. Fauzi, "Comparison of tree implementation, regression logistics, and random forest to detect iris types," TAM (Technology Acceptance Model) Journal, vol. 12, no. 2, pp. 149–157, 2021.

[30] R. V. Anand, A. Q. Md, S. Urooj, S. Mohan, M. A. Alawad, and A. C., “Enhancing diagnostic decision-making: Ensemble learning techniques for reliable stress level classification,” *Diagnostics*, vol. 13, no. 22, p. 3455, 2023, doi: 10.3390/diagnostics13223455