

Early Detection System for Heartbeat Abnormalities in Autistic Children Using Support Vector Machine

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Abstract: This research aims to develop an early detection system for heart rate anomalies in autistic children based on Heart Rate Variability (HRV) to prevent tantrum behavior that can endanger the child's physical and psychological health. Based on previous research, children with autism spectrum disorder (ASD) show a significant increase in heart rate (HR), especially when experiencing stress or anxiety, with some cases reaching above 120 bpm. At the same time, control groups such as children with language disorders do not show a similar pattern. This leads to the hypothesis that physiological monitoring using non-invasive technologies, such as Photoplethysmography (PPG), can detect changes in HR before a tantrum occurs. The purpose of this study is to design a wearable device based on a pulse sensor and NodeMCU that can integrate HR in real-time, extract HRV features in the frequency domain (VLF, LF, HF, and LF/HF ratio), and classify normal and anomalous conditions using the Support Vector Machine (SVM) algorithm. The system is designed to notify parents or caregivers via a Telegram bot when HR exceeds 114 bpm. The research methodology was experimental, conducted on two subjects: a 7-year-old boy and a girl on the autism spectrum during learning, quiet, and tantrum activities. Results showed that HRV parameters increased significantly during the tantrum condition and even during learning, indicating activation of the sympathetic nervous system. The SVM classifier achieved 98.9% accuracy in the tantrum condition, 82% in the learning condition, but only 61.1% in the transition from quiet to tantrum. Overall, the system proved effective at detecting hyperactivity but still requires further development regarding data volume, subject variation, and improvements in accuracy during the transition phase for widespread implementation.

Keywords: Autism Spectrum Disorder (ASD); Early Detection System; Heart Rate Variability (HRV); Photoplethysmography (PPG); Support Vector Machine (SVM)

INTRODUCTION

Autism Spectrum Disorder (ASD) is a complex developmental disorder, classified as exceptional children who are very diverse, insecure, aggressive, less responsive or even excessive to external stimuli, and move their limbs unnaturally and can affect their behavior, namely tantrums (Beauchamp-Châtel et al., 2019). According to the Director of Mental Health Development of the Ministry of Health in 2013, an estimated 112,000 children in Indonesia have autism, in the age range of around 5-19 years (Farahdina et al., 2025). Autistic children have difficulty understanding emotions and feelings. They are sometimes tough to control, making it difficult for them to conclude when they are experiencing tantrums due to emotional disorders or others (Aldabas, 2019).

One cause of tantrum behavior in children is unfulfilled desires and limited language skills to express their feelings. In some instances, tantrums can be caused by behavioral disorders or psychological problems, such as in autistic children (Deichmann & Ahnert, 2021). To clarify the definition of tantrums, it is found that tantrums are destructive behaviors in the form of physical outbursts, (e.g., hitting, biting, pushing) or verbal outbursts (e.g., crying, screaming, whining), or continuous sulking, that can injure oneself or others (Awanda Amelia Sadita & Nurus Sa'adah, 2023). Emotional disorders that are continuous and cause tantrums will hurt the physical condition of autistic children, such as increased blood flow, high blood pressure, and even heart attacks (Tsai et al., 2025).

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Human organs work consciously and unconsciously. The heart is an internal organ in humans that works unconsciously. The human nervous system consists of two parts, namely the somatic nervous system (SoNS) and the autonomic nervous system. The ANS is divided into two parts, namely the parasympathetic nervous system and the sympathetic nervous system (Tsai et al., 2025). The sympathetic nervous system works by accelerating organ function, such as increasing heart rate and lowering blood pressure. Meanwhile, the parasympathetic nervous system slows the function of human organs by inhibiting heart rate and increasing blood pressure (McCorry, 2007).

Heart rate variability (HRV) is the variation in the time intervals between consecutive heartbeats and reflects the balance between sympathetic and parasympathetic activity (Pinge et al., 2022). Continuous changes in sympathetic and parasympathetic nerve impulses alter heart rate. One analytical method for HRV is frequency-domain analysis (Chen et al., 2019). Variation between consecutive heartbeats is needed to detect tantrums, as HRV reflects the balance between the two nervous systems. Heart rate (HR) is the heart rate per unit of time measured in beats per minute (BPM). BPM data can be collected using an electrocardiogram (ECG), a photoplethysmograph (PPG) device, and a chest strap (Zhang et al., 2019). PPG-based sensors are often used for long-term HR monitoring with wearable devices rather than ECG electrodes due to their convenience and reliability (Weiler et al., 2017).

In the study (Novani et al., 2019), PPG was used to classify human stress levels using HRV. The results with a total of 80 training data, in mild stress training with a total of 19 training data, had an accuracy of 95%, in moderate stress training with a total of 49 training data had an accuracy of 96%, and in moderate stress training with a total of 12 training data had an accuracy of 99%. In another study (Islmabouli et al., 2025), related to the analysis of stress levels in children with autism spectrum disorder (ASD) and language disorder (LD), using the ADOS-2 method (The Autism Diagnostic Observation Schedule-second edition), it was found that the Heart Rate of autistic children was significantly higher than the HR of children with language disorder during interactive activities. Furthermore, the authors observed that autistic children more often approached the upper limit of the normal HR range (95-140 bpm) in the 3-5 years age group, with an average of 4 patients above 120 bpm in the autistic children group and 0 in the language disorder group. Based on the explanation above, the researchers hypothesize that the PPG device can be applied as a simple, non-invasive technology to detect heart rate when a tantrum is about to occur in autistic children. Heart rate detection in autistic children will make it easier to detect abnormal heart rate changes, even leading to a tantrum, and thus enable them to receive specialized treatment from parents or loved ones.

LITERATURE REVIEW

Research on detecting heart rate abnormalities using the Heart Rate Variability method has been widely conducted. In this research (Fioriello et al., 2020), related to the analysis of stress levels in children with autism spectrum disorder (ASD) and language disorder (LD) using the ADOS-2 (The Autism Diagnostic Observation Schedule, second edition) method, and found that the Heart Rate of children with ASD was significantly higher than the HR of children with LD during interactive activities. Furthermore, the authors also observed that children with ASD were more often close to the upper limit of the normal HR range of 95-140 bpm for ages 3-5 years, with an average of 4 patients above 120 bpm in the ASD group and 0 patients in the LD group.

In another study (Thapa et al., 2021), aimed to examine the relationship between resting-state HRV, medication use, and symptom severity in children diagnosed with autism. Children with autism, aged 3 to 12 years, were compared with 44 neurotypical children of the same age. Laboratory assessment of HRV involved a 5-minute non-invasive baseline electrocardiogram measurement while participants watched an age-appropriate, non-verbal animated video. Results from this study showed that across most time- and frequency-domain measures of the parasympathetic nervous system (HRV HF; RMSSD HRV), children diagnosed with autism showed decreased HRV. This was associated with small to medium effect sizes ($d = 0.43$ and $d = 0.41$, respectively).

Another study (Novani et al., 2018), examines the use of HRV measurements to classify mental stress and health conditions in subjects with influenza-related conditions using the frequency-domain method. Classification results for two different test subjects yielded 94% and 75% accuracy in classifying influenza for each subject. For stress classification, using training and testing data from each subject, 81% and 66% accuracy were achieved, respectively. Another research (Weiler et al., 2017), aimed to compare the average HR readings from two different HR technologies (PPG vs. ECG) after cardio-based interval training. Results showed no significant difference between the two technologies. However, when HR reached approximately 155-160 beats per minute, the difference was approximately 5 beats per minute.

The research mentioned above has focused on analyzing heartbeats in adults and children with autism. No research has yet combined heartbeat analysis with artificial intelligence. This study aims to classify heartbeat abnormalities in children with autism using machine learning. Furthermore, it seeks to identify biosignals and

abnormalities in these biosignals when tantrums are imminent in children on the autism spectrum, enabling preventive measures to be taken to avoid serious health consequences.

METHOD

1. General System Design

The general design scheme for this system is a child with autism spectrum disorder (ASD) who will be the device's user, as shown in Figure 1. The device, shaped like a wristband, will be used on the child's left/right wrist to get the child's heart rate. Next, the heart rate sensor will continuously monitor the child's heart rate and alert if anomalies or early symptoms of tantrums are detected. Then the sensor data will be sent to the microcontroller for processing with the ADC, so that a digital value corresponding to the autistic child's condition is obtained, and the RR Interval value is stored in a CSV file. After the CSV file is received, it will be imported into MATLAB for processing into HRV frequency-domain features. After the HRV extraction feature value is obtained, classification will be performed using the SVM algorithm.

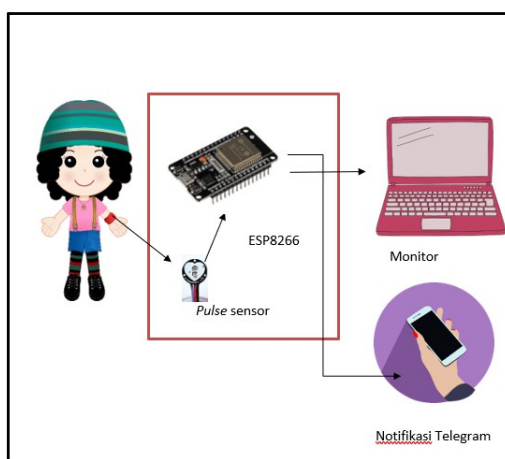


Fig. 1 General System Design Scheme

2. Process System Design

In the process design, the working process of the system functionality to be created will be explained, starting from data reading by the sensor to the output results obtained by the user. The general system functionality flow is shown in Figure 2. Based on the design process flow diagram, the process starts with the pulse sensor detecting the signal, converts it through the ADC to obtain the RR interval, and then stores the RRI data in a CSV file. After that, the file will be imported into MATLAB and continued with feature extraction. The training data will then be used to train the SVM classification model. In the second flowchart, the test data will be processed using the trained model to obtain classification results.

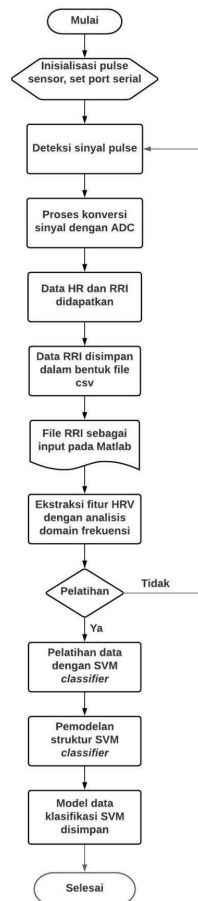


Fig. 2 Training Data Process Design Flow Diagram

3. Hardware Design

In the hardware design, a pulse sensor will be attached to the autistic child's wrist with an ESP8266 connected to it, as shown in Figure 3. The signal captured by the pulse sensor will then be processed on the monitor. In MATLAB, RR-Interval data will be input, and feature extraction will be performed. The smartphone device will provide a warning via a Telegram bot if the autistic child's HR condition is abnormal.

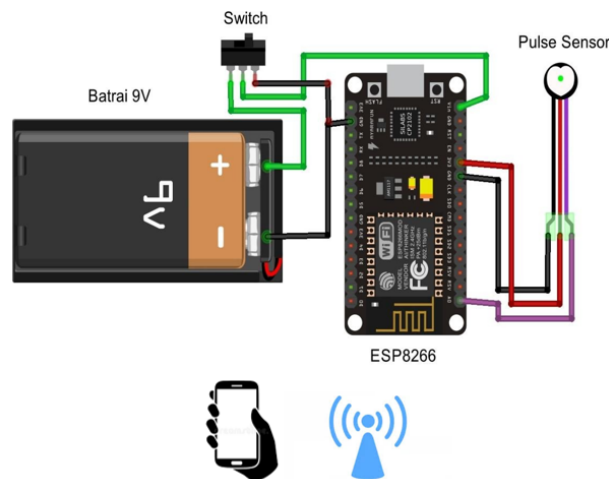


Fig. 3 Hardware Design

4. Data Acquisition and Training with SVM Modeling

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In this process, data collection and training will be required to test the SVM model. This SVM model can classify both the training and test data, as shown in Figure 4. The training data is the data used to train the system being created. The training data consists of 300 data points collected over 5 minutes from HR data of autistic children. Meanwhile, the test data is the data used in testing the SVM classifier modeling system.

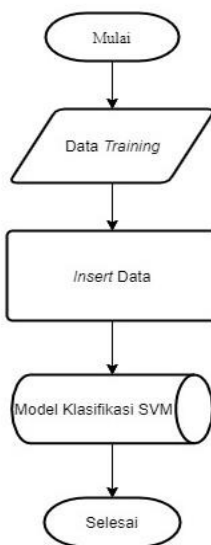


Fig. 4 Data Collection and Training Design with SVM Modeling

After the SVM classification model is created, the next step is to input the test data to be processed with the SVM classification model. This results in the classification results from the test data.

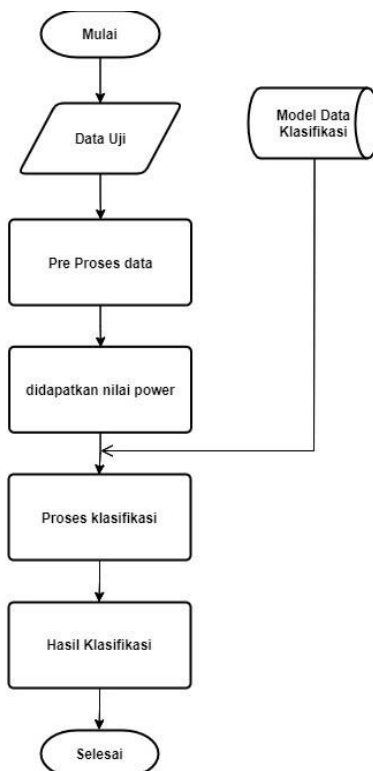


Fig. 5 Test Data Flow Diagram with SVM Modeling

RESULT

1. Hardware Implementation

The hardware implementation consists of a pulse sensor to detect heart rate and an ESP8266 NodeMCU microcontroller to process the pulse sensor signal and serve as a connector to the Telegram bot. These components will be installed in a small watch-shaped box measuring 34 mm long, 50 mm wide, and 28 mm high, and weighing 105 g. This prototype will be attached to the wrist of an autistic child. The hardware implementation for this study is shown in Figure 6.

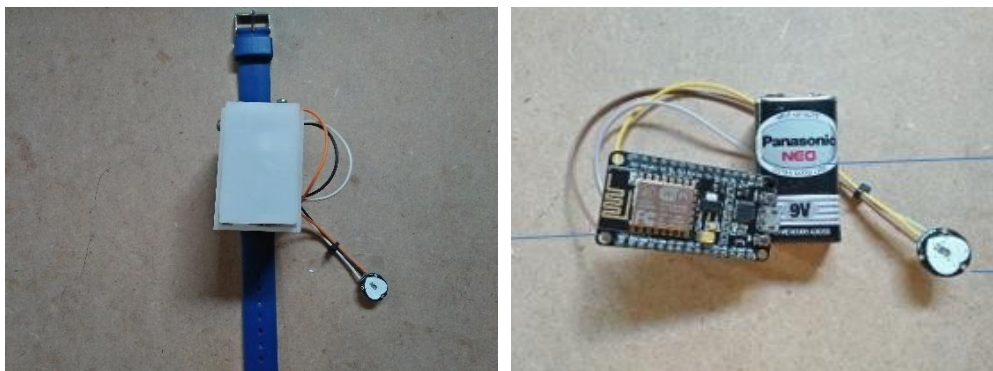


Fig. 6 Hardware Implementation in Prototype Form

This system works through the Arduino IDE, software that processes data from sensors and controls other devices connected to the microcontroller. In this system, NodeMCU ESP8266 is used. Then MATLAB, which is software used to process training and test data using support vector machine (SVM) modeling, as well as a GUI (Graphical User Interface) that displays the distributions of training and test data and classification results. Finally, as a Telegram Bot warning, which is software used to display notifications about the heart rate of autistic children if an anomaly occurs.

2. Pulse Sensor Testing

The pulse sensor was tested by detecting a heartbeat. The pulse sensor was compared with the Polar OH1+. The Polar OH1+ pulse sensor was attached to the wrist. The Polar OH1+ is an optical heart rate sensor that can measure heart rate in BPM from the wrist. The pulse sensor was tested by capturing data for 15 seconds from the pulse sensor and the Polar. The test results are shown in Table I.

Table I. Comparison of HR Data from Polar OH1+ and Pulse sensor Readings

Testing the-	Polar OH1+ (Bpm)	Pulse Sensor (Bpm)	Percentage Difference in Reading	Polar OH1+ (Bpm)	Pulse Sensor (Bpm)	Percentage Difference in Reading
	Women			Men		
1	96	107	11.45%	60	65	8.33%
2	94	73	21.5%	53	59	11.3%
3	97	133	37.11%	65	68	4.6%
4	98	101	3.06%	58	59	1.7%
5	92	96	4.34%	54	62	14.8%
6	93	84	9.67%	60	60	0
7	101	92	8.91%	62	66	6.4%
8	95	92	3.15%	63	66	4.7%
9	92	85	7.6%	55	51	7.2%
10	95	95	0	53	50	5.6%
11	89	79	11.23%	51	50	1.9%
12	94	87	7.44%	53	55	3.7%
13	95	108	13.68%	54	50	7.4%
14	92	95	3.26%	57	56	1.7%

15	95	91	4.21%	60	63	5%
Total Errors (%)		146.61%		Total Errors (%)		84.33%
Average Error (%)		9.774%		Average Error (%)		5.622%

Based on the test data in Table I, to determine the percentage error from the pulse sensor reading results, the following formula can be used:

$$\begin{aligned}
 \text{Percentage of Error} &= \frac{\text{Pulse Sensor Reading} - \text{Polar OH1+ Reading}}{\text{Polar OH1+ Reading}} \times 100\% \quad (1) \\
 &= \frac{107 - 96}{96} \times 100\% = 11.45\%
 \end{aligned}$$

To find out the percentage of accuracy of the pulse sensor, you can use the following formula:

a. Female test object

$$\text{sensor accuracy} = 100\% - \left(\frac{\text{Total Errors (\%)}}{\text{Number of Trials}} \right) \quad (2)$$

$$\text{sensor accuracy} = 100\% - \left(\frac{146.61 (\%)}{15} \right)$$

$$\text{sensor accuracy} = 100\% - 9.774\%$$

$$\text{sensor accuracy} = 90.22\%$$

b. Male test object

$$\text{sensor accuracy} = 100\% - \left(\frac{\text{Total Errors (\%)}}{\text{Number of Trials}} \right) \quad (3)$$

$$\text{sensor accuracy} = 100\% - \left(\frac{84.33 (\%)}{15} \right)$$

$$\text{sensor accuracy} = 100\% - 5.622\%$$

$$\text{sensor accuracy} = 94.3\%$$

The average error value was 9.774% for female test subjects and 5.622% for male test subjects. Therefore, the sensor's accuracy in measuring heart rate was 90.22% for female test subjects and 94.3% for male test subjects. The comparison of HR data from the Polar OH1+ and the Pulse sensor is shown in Figure 7. Testing the pulse sensor on different test objects showed that its accuracy was above 90%. Therefore, the pulse sensor can be implemented for heart rate measurement.

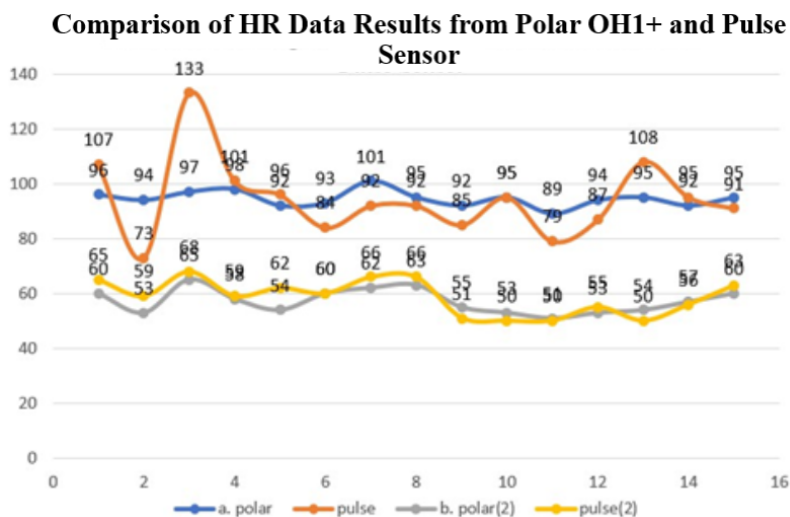


Fig. 7 Comparison Chart of HR Data Results from the Polar OH1+ and Pulse Sensor; a. Women, b. Men

3. Testing the Results of Normal and Anomalous Heart Rate Classification

Classification testing aims to determine the accuracy of the designed system. Classification testing compares the classification model's output in the GUI with the observed data. The test data consists of three activities performed by an autistic child. The comparison is made by looking at HR values recorded over 5 minutes, then labeling them as usual (below 114 Bpm) or anomalous (above 114 Bpm). The comparison of the classification data is shown in Table II.

Table II. Comparison of Normal and Anomalous Heart Rate Classification Results

Experimental Conditions	Classification Results from Heart Rate Monitoring	Classification Results of the System in MATLAB
Tantrum Condition	295 Anomalies, 5 Normal	300 Predicted Data Anomalies.
Conditions from Rest to Tantrum	131 Anomalies, 169 Normal	297 Data Predicted Anomalous, 3 Data Predicted Normal
Learning Conditions	212 Anomalies, 88 Normal	300 Predicted Data Anomalies.

4. Telegram Bot Testing and Analysis

Telegram bot testing was conducted to determine whether the bot could provide accurate notifications and comply with system commands. The first test involved sending ten test messages to the bot and then observing the average response time. The test results are shown in Figure 8 and Table III.



Fig. 8 Telegram Bot Test Results

Table III. Telegram Bot Test Results

Testing the-	Notification Delivery	Response Time (Seconds)	Information
1	Message Sent	1.57	Succeed
2	Message Sent	1.51	Succeed
3	Message Sent	1.34	Succeed
4	Message Sent	1.38	Succeed
5	Message Sent	1.37	Succeed
6	Message Sent	1.29	Succeed
7	Message Sent	1.28	Succeed
8	Message Sent	1.57	Succeed

9	Message Sent	1.23	Succeed
10	Message Sent	1.13	Succeed
Average Response Time (Seconds)		1.367 seconds	

The bot test results in Table 2 show that the success rate for sending notifications to the Telegram bot reached 100%, with an average response time of 1.367 seconds. This test is considered successful if the notification sent to the Telegram bot appears in the Telegram bot interface.

5. Analysis of the Effect of Feature Extraction Values on Stress Conditions in Several Activities of Autistic Children

The relationship between HRV and stress is driven by variations in HRV, specifically low parasympathetic activity, characterized by decreased HF and increased LF. Measures of PNS activity characterize HF; for example, it slows heart rate and decreases adrenaline secretion, whereas LF reflects SNS activity, which functions inversely to the PNS. The results of cardiac autonomic measurements indicate that children with autism exhibit decreased parasympathetic activity, increased sympathetic activity, and therefore an increase in sympathovagal balance. This is reflected in lower HF HRV indices and higher LF and LF/HF ratios among ASD. Table IV presents a comparison of frequency-domain values across data sets, adjusted for several activities in children with autism.

Table. IV Comparison of Domain Frequency of Each Activity

Activity	VLF	LF	HF	Ratio LF/HF
(I) Resting Condition	0.5164	0.1409	0.0065	21.79
(II) Tantrum Condition	0.1619	0.0931	0.0042	22.1380
(III) Conditions from Rest to Tantrum	102.0286	0.0087	0.00003614	23.83
(IV) Learning Conditions	0.6413	0.3065	0.0069	44.6624

From the results in Table 4, the LF/HF ratio increases in each activity series compared to the LF/HF ratio in the training data (8.4849 ms²). To determine the presence of a stress response to each activity, it can be seen that in activity (I), the LF value increased, while the HF value decreased. This indicates a stress response during resting conditions in autistic children. HRV will decrease if parasympathetic activity is lower than sympathetic activity. Therefore, activity (I) shows a lower HRV.

In activity (II), the LF value increased compared to the low HF value. This condition shows greater sympathetic than parasympathetic activity. And in activity (II), HRV is lower. In activity (III), a mixed activity from rest to tantrum conditions, the stress response is characterized by lower HRV and a higher LF than HF. In activity (IV), the same thing happens, indicating a lower HRV with a greater LF than HF. In condition (IV), the stress level is higher than in other activities, which is seen from the comparison of LF values from each activity. In condition (IV), the LF value is the highest of all other conditions, namely 0.3065 ms².

6. Evaluation Performance of SVM Model with Testing Data

Testing the SVM model involved assessing its performance and classification accuracy. To test the model's performance, 300 data points were extracted from each activity of the autistic child. The classification model's predictive accuracy is presented in a confusion matrix as shown in Table V.

Table. V Test Results Test Data

Prediction	Actual			F1-Score	Condition
		1	0		
1	TP=295	FP=5	98.9%	Tantrum condition	
	0	FN=0			TN=0
0	TP=131	FP=166	61.1%	Conditions from rest to tantrum	
	0	FN=0			TN=3
1	TP=212	FP=88	82%	Learning conditions	
	0	FN=0			TN=0

After conducting testing of each test data, the next step is to display the percentage table of performance evaluation of the test data.

Table. VI Evaluation of Test Data Performance under Tantrum Conditions

Classification Results	Data Testing
Total data	300
True Positive (TP)	295
False Positif (FP)	5
True Negative (TN)	0
False Negative (FN)	0
Sensitivity = $TP/(TP+FN)$	100%
Precision = $TP/(TP+FP)$	98.3%
Accuracy = $(TN+TP)/(TP+TN+FP+FN)$	98.3%
F1-Score = $2*Sensitivity*Precision/(Sensitivity + Precision)$	98.9%

Table. VII Evaluation of Test Data Performance under Rest to Tantrum Conditions

Classification Results	Data Testing
Total data	300
True Positive (TP)	131
False Positif (FP)	166
True Negative (TN)	3
False Negative (FN)	0
Sensitivity = $TP/(TP+FN)$	100%
Precision = $TP/(TP+FP)$	44%
Accuracy = $(TN+TP)/(TP+TN+FP+FN)$	44.6%
F1-Score = $2*Sensitivity*Precision/(Sensitivity + Precision)$	61.1%

Table. VIII Evaluation of Test Data Performance under Learning Conditions

Classification Results	Data Testing
Total data	300
True Positive (TP)	212
False Positif (FP)	88
True Negative (TN)	0
False Negative (FN)	0
Sensitivity = $TP/(TP+FN)$	100%
Precision = $TP/(TP+FP)$	70%
Accuracy = $(TN+TP)/(TP+TN+FP+FN)$	70%
F1-Score = $2*Sensitivity*Precision/(Sensitivity + Precision)$	82%

To benchmark algorithm performance, select an algorithm with high accuracy if the dataset has roughly equal numbers of false negatives (FN) and false positives (FP). If the numbers are not close, use the F1-Score as a reference in selecting good performance. The table shows that the f1-score for the tantrum condition is 98.9%, for the rest-to-tantrum condition is 61.1%, and for the learning condition is 82%.

7. Microcontroller Network Communication Testing

Testing on the ESP8266 NodeMCU was conducted to determine the maximum range of the Wi-Fi network used in the system. Testing was carried out by testing the Wi-Fi communication network from the board at a range of more than 20 m, as shown in Table IX.

Table. IX Wifi Communication Range Testing of the System

Distance (Meters)	Room Condition		System Detection Results	
1m	Open	Close	Success	Success
5m	Open	Close	Success	Success
10m	Open	Close	Success	Success
15m	Open	Close	Success	Success

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20m	Open	Close	Success	Failure
25m	Open	Close	Success	Failure
30m	Open	Close	Success	Failure

8. Overall System Testing

The overall system testing aimed to determine whether the designed system was appropriate and functioning correctly, and whether it could notify the Telegram bot if an anomaly in the heartbeat of an autistic child were detected. This testing was conducted by attaching a device to the wrist of an autistic child during the learning and therapy process at the Bina Anggita Special School for Autism in Yogyakarta, as shown in Figure 9. The results of the system testing are shown in Table X.



Fig. 9 Device Testing on Autistic Students

Table. X Overall Tool Testing

Testing Time	Condition of Autistic Children	Telegram Bot Notifications	Information
10.32	Calm	Anomaly Detected	Not Successful
10.32	Calm	Anomaly Detected	Not Successful
10.34	Restless (Whining)	Anomaly Detected	Successful
10.35	Restless (Whining)	Anomaly Detected	Successful
10.35	Restless (Whining)	Anomaly Detected	Successful
10.36	Restless (Whining)	Anomaly Detected	Successful
10.36	Restless (Whining)	Anomaly Detected	Successful
10.37	Restless (Whining)	Anomaly Detected	Successful
10.37	Restless (Whining)	Anomaly Detected	Successful
10.38	Restless (Whining)	Anomaly Detected	Successful
10.39	Restless (Whining)	Anomaly Detected	Successful
10.40	Restless (Whining)	Anomaly Detected	Successful
10.41	Restless (Whining)	Anomaly Detected	Successful
10.44	Restless (Whining)	Anomaly Detected	Successful
10.45	Restless (Whining)	Anomaly Detected	Successful
10.48	Restless (Whining)	Anomaly Detected	Successful
10.51	Restless (Whining and Shouting)	No Notification	Not Successful
10.53	Restless (Whining and Shouting)	No Notification	Not Successful
10.55	Restless (Whining and Shouting)	No Notification	Not Successful
10.56	Restless (Whining)	Anomaly Detected	Successful

$$\begin{aligned}
 \text{Success Percentage} &= \frac{\text{Number of Successful Trials}}{\text{Total Number of Trials}} \times 100\% & (4) \\
 &= \frac{16}{20} \times 100 = 80\%
 \end{aligned}$$

Based on the tests conducted, the system achieved an 80% success rate in detecting heart rate anomalies in autistic children. This system test demonstrates its ability to detect heart rate anomalies successfully and provides sufficient performance to be implemented with autistic children.

DISCUSSIONS

According to the experimental findings performed in this work, some analysis and interpretation of the results can be made: mainly on finding heart rate anomalies for autistic children with Heart Rate Variability (HRV) approach (non-invasively form) means and Support Vector Machine (Classification-SVM). This conversation includes comparison of measured and modeled data, examination of the overall efficacy of the systems being considered, and what these findings mean for the science as well as technical issues addressed. During the system testing phase, heart rate measurements using a pulse sensor were compared with those of the Polar OH1+ reference device, a high-accuracy photoplethysmography (PPG)-based optical heart rate sensor. The results showed that heart rate readings from both devices were relatively close, although there were slight deviations under some conditions. This indicates that the pulse sensor is sufficiently accurate for non-invasive applications in children, especially for short-term, real-time monitoring.

Furthermore, the classification results for normal and anomalous heart rates from the SVM-based system were compared with direct observation data based on a threshold of 114 bpm. Across three activity scenarios—tantrums, transitions from rest to tantrum, and learning—the system achieved varying success rates in classifying all test data as anomalies: 98.9% in the tantrum condition, 61.1% in the rest-to-tantrum condition, and 82% in the learning condition. This finding is interesting because, although HRV is often associated with stress or negative emotions, learning also exhibits increased sympathetic activity, reflected in increases in LF (Low Frequency), HF (High Frequency), and the LF/HF ratio. This suggests that cognitive stimulation can also trigger significant physiological responses in autistic children, enabling the system to detect not only tantrums but also high-stress situations that warrant monitoring.

One of the most significant findings of this study is that increases in frequency-domain HRV (especially LF and the LF/HF ratio) occur not only during tantrums but also during learning in autistic children. This provides new insight that intensive cognitive activity can lead to increased autonomic nervous system activity, similar to a stress response. Thus, an HRV-based detection system is not only helpful for predicting tantrum behavior but can also be used to assess mental stress during therapy or learning.

Furthermore, the system's integration with a Telegram bot successfully provided real-time notifications to parents or caregivers when the heart rate exceeded a threshold (≥ 114 bpm). Distance testing demonstrated that the system remained functional up to 95 meters in a closed room, which is sufficient for home or school environments. However, WiFi signal interference beyond 95 meters is a significant limitation that needs to be addressed by using alternative communication modules, such as LoRa or BLE, in future development.

Technically, this research successfully demonstrated that a NodeMCU and pulse sensor-based wearable device can be designed and effectively used to monitor the physiological conditions of autistic children. However, to improve the validity and reliability of the system, it is recommended to increase the number of test subjects with varying ages, genders, and autism severity, use higher-quality PPG sensors or a combination with ECG for more accurate validation, apply other classification methods such as Random Forest, Neural Network, or LSTM to compare the accuracy and robustness of the model and develop a dedicated mobile application that is more informative than the Telegram bot, including HRV visualization, heart rate history, and intervention recommendations.

Overall, this research successfully designed and implemented a heart rate anomaly detection system in autistic children based on HRV and SVM, capable of providing early warnings via Telegram notifications. Despite limitations in data coverage and accuracy during the transition phase, the findings of increased autonomic activity during learning activities open new opportunities for understanding the physiological dynamics of autistic children. This system has the potential to be a valuable tool for parents, therapists, and educators, enabling timely and personalized interventions.

CONCLUSION

This research successfully designed and implemented a wearable device-based heart rate anomaly detection system for autistic children using the Heart Rate Variability (HRV) method and Support Vector Machine (SVM) classification. The developed system consists of a pulse sensor module to measure heart rate, a NodeMCU (ESP8266) microcontroller to process data, and integration with a Telegram bot for real-time notifications to parents or caregivers. Through frequency domain analysis of HRV—including Very Low Frequency (VLF), Low

Frequency (LF), High Frequency (HF), and the LF/HF ratio—deep physiological insights were gained into the autonomic nervous system responses of autistic children to various activities.

The results showed that HRV parameters, particularly LF, HF, and the LF/HF ratio, increased significantly not only during tantrums but also during learning. These findings provide new insights into how even intensive cognitive activity can trigger sympathetic activation, similar to the stress response. This underscores the importance of physiological monitoring not only in extreme emotional situations but also during the learning process to prevent mental fatigue or overstimulation.

The SVM-based classification system identified anomalous conditions with varying success rates: 98.9% in the tantrum condition, 61.1% in the transition from silence to tantrum, and 82% in the learning condition. These results indicate that the system is very effective at detecting hyperactive conditions but still has limitations in recognizing the early phase of physiological changes (transitions), likely due to a lack of training data on these conditions and to the model's inability to fully capture the dynamics of body responses.

This research offers tangible benefits for early intervention and behavioral management of autistic children. With a Telegram-based notification system, parents and therapists can immediately respond to a child's unstable physiological state, enabling preventive measures such as distraction, relaxation techniques, or rest. Furthermore, this system can be used as a tool in inclusive schools or therapy centers to assess a child's mental stress during daily activities. More broadly, the developed approach can be adapted for other applications, such as stress detection in other neurodivergent children, monitoring student mental health, or providing alert systems for anxiety disorders.

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