VOL. 23, NO. 2, 2024, 1-9
elektrika.utm.my
ISSN 0128-4428

ELEKTRIKA
Journal of Electrical Engineering

Emotion Classification System for ASD Group by Using Wireless EEG Monitoring Device

Soh Ghee Hou and **Mohd Ridzuan bin Ahmad***

Department of Control and Mechatronics Engineering, Faculty of Electrical Engineering, Universiti Teknologi Malaysia, 81310 Skudai, Johor, Malaysia.

*Corresponding author: mdridzuan@utm.my

Abstract: This paper delves into a study employing dry electroencephalograms (EEG) as input features to discern emotions in individuals with autism spectrum disorders (ASD). While EEG is a prevalent tool in emotion classification studies for typically developing individuals, less attention has been directed towards its application in the ASD population. In this study, ten participants diagnosed with ASD wore wireless dry EEG sensors to capture their EEG signals. These signals encompassed alpha, beta, delta, theta, and gamma waves, which were subsequently subjected to feature extraction techniques such as the t-test, principal component analysis (PCA), ReliefF, and Chi-Square. Classification of positive, neutral, and negative emotions was performed using various algorithms, including K-nearest neighbor (KNN), Multinomial Logistic Regression (MLR), Naive Bayes (NB), Random Tree (RT), Random Forest (RF), and Support Vector Machine (SVM). Ultimately, employing SVM with a t-test enhanced the accuracy of emotion classification for the ASD group from 66.4% to 74.1%.

Keywords: EEG, ASD, Emotion, Feature Extraction, Machine Learning

Article History: received 18 April 2023; accepted 9 July 2024; published 29 August 2024

1. INTRODUCTION

A neurodevelopmental condition known as autism spectrum disorder (ASD) is characterized by restricted or repetitive behaviors, persistent speech problems, and decreased social interaction [1]. Asperger syndrome, pervasive developmental disorder, childhood disintegrative disorder, and autistic disorder are the subcategories of ASD [2].

Repetitive behaviors, a limited range of interests, communication difficulties, and social interaction deficits such as reduced facial expression, body movements, and eye contact are the three main characteristics of autism spectrum disorder [3]. Additionally, although autistic children prefer to express their emotions in ways comparable to typically developing children, they frequently struggle in school to express their feelings and are misinterpreted by their peers.

Additionally, some research suggests that autistic children struggle to memorize gaze, face, and facial movements and cannot imitate body movements or behaviors [4, 5]. Social interaction and emotional processing are closely related [6], and social difficulties could arise in ASD if the emotional recognition system is changed [7]. Most autistic kids have trouble integrating their emotional and sensory sensitivity [8]. A neurofeedback or psychologist doctor can quickly identify inaccurate judgments if the brain is in a particular performance condition by obtaining a description of symptoms and completing the initial interview forms. They were developing a therapy that addresses emotional sickness's underlying and differential processes to broaden its appeal. A more extensive range of symptom presentations and diagnostic criteria may be compatible with emotion-centered therapy. A stronger emotional emphasis may make it easier for the therapy to be generalized or translated, increasing the treatment's effectiveness by better mirroring the presentations of concomitant disorders [9].

Face expression recognition [10], electrodermal activity [11], speech recognition [12], electroencephalogram [EEG], and multi-model emotion recognition systems [13, 14] are some of the existing methods for identifying human emotion. Since a dry EEG sensor is unaffected by ambient factors, including temperature, illumination, body posture, and noise, it is employed in this study to collect brainwaves from both the autistic group. Thus, ASD therapists can obtain the best therapy performance using Electroencephalogram (EEG) biofeedback.

For the best therapeutic results, ASD therapists might use electroencephalogram (EEG) biofeedback. The psychophysiological characteristics of autistic people can be effectively treated with electroencephalogram (EEG) neurofeedback [15], and these non-invasive, successful therapies make ASD treatment very desirable [16]. All of our ideas originate from our emotions and behaviors, which also serve as the foundation for neural communication in the brain. Coordinated electrical impulses between multiple connected neurons produce brain waves.

Due to its high accuracy, electroencephalography (EEG) is one of the most popular techniques for categorizing emotions. However, the setup procedure is time-consuming and noise-sensitive. There are 21 recording electrodes, each requiring skin-to-skin contact with the head to ensure low-noise features. [17]. According to a previous study, strong valence was linked to high frontal alpha or right parietal beta power [18]. Positive emotion shows significant frontal left activity, while negative emotion indicates high frontal proper activation [19].

The effectiveness and enormous diagnostic potential of computer analysis of non-invasive recording features for autistic patients, such as magnetoencephalography, have increased [20]. The utilization of feedback from patients' unique bioelectrical features in structuring treatment interventions to achieve extreme personalization is a characteristic of these technologies [21]. Brainwave frequencies are banded to distinguish between slow, moderate, and fast waves and were measured in Hertz (cycles per second). There are five EEG bands: beta (12–30 Hz), alpha (8–12 Hz), theta (4–8 Hz), and gamma (30–42 Hz), but the definitions of these bands vary depending on the research. These frequencies represent the various states and functions of the brain. The cortical topography, processes, and physiology differ depending on the state [22].

Using a clinical EEG sensor, emotions can identified with great accuracy. However, because of its lengthy setup procedure and noise sensitivity, it is best used in clinical situations. Fast response time is another benefit of clinical EEG-based emotion categorization and good classification accuracy. Additionally, it enables the collection of information on individuals with impairments such as facial paralysis or a lack of facial expression of emotion [19].

Clinical EEG has certain drawbacks, including slower setup times than other emotion identification techniques. The resistance needs to be less than 5 k ohm for the clinical EEG, so conductive fluid is required between the person and the wet EEG. The amplitude of the EEG signal increases with decreasing electrode impedance [23]. The size of the clinical EEG limits where the data can be collected or tested (lab). Since the clinical EEG needs to wrap around the patient's head, it will make autistic patients more anxious. As a result, more people favor wireless EEG monitoring devices over clinical EEG monitoring devices [24].

Since the clinical EEG sensor must be wrapped around the patient's skull, this will make autistic patients more anxious. Most autistic patients prefer wireless and compact EEG monitoring devices over clinical EEG sensors despite the clinical EEG sensor's lesser accuracy than the wireless dry EEG monitoring device [25]. Consequently, this study harnessed the capabilities of a wireless dry EEG sensor to explore the nuances in EEG signals among individuals with ASD across various emotional experiences.

2. METHODOLOGY

This study was divided into four domains: EEG signal acquiring, EEG signal preprocessing, EEG signal features extraction, and EEG signal classification. There are a few main stages to analyze subjects' EEG signals in this study in a different emotion. Firstly, a wireless EEG monitoring device – MUSE 2- was used to acquire the subjects' EEG signals. Then, the EEG signals were re-referenced to an average mastoid and filtered using a Butterworth filter with a bandpass of 0.1 Hz to 45 Hz before a 50 Hz notch filter was applied to remove the noise from the power supply. After preprocessing the EEG signals, a feature extraction technique was applied to extract the important features. The essential elements will used for emotion classification by using machine learning methods. To gauge the effectiveness of the emotion classification module, the accuracy of the trained model underwent evaluation.

2.1 Acquire Raw EEG Data

The wireless EEG monitoring device (MUSE 2 from InteraXon Inc.) was used in this research to measure the brainwaves of autistic patients, such as Alpha, Beta, Theta, Gamma, and Delta waves. In addition, the sensor is also able to measure heart rate (PPG + pulse oximetry), body position (accelerometer), and breath rate (PPG + gyroscope). Figure 1 shows the location of the electrodes in MUSE 2 and MUSE EEG headset electrodeposition.

The TD group is defined as people functioning well in physical, cognitive, social/ emotional, and communication [26]. All TD participants in this study had fine motor skills, mental ability, and articulateness, and they did not face any emotional difficulty.

The EEG signals were recorded using four electrode pads, TP9, AF7, AF8, and TP10, with Fpz as a reference. In a previous study [27], Gamma waves at TP9 and TP10 significantly changed when emotion changed. Gamma waves at TP9 and AF7 will substantially differ between neutral and fear. Meanwhile, there were also significant differences when participants' feelings changed from neutral to disgust for TP10 and AF8.

All subjects used the same device to record the EEG signal to ensure the reliability of the result. In addition, the participants were requested to watch their favorite video based on a survey form filled out by participant parents and therapists to stimulate and investigate the positive emotions and collect the emotion data. The facial emotion of each participant was observed, and the recorded outputs were based on the facial emotion expression. In addition, the subjects were asked to fill out the survey form to understand their favorite things, hobbies, daily habits, dislike of objects, and how to console autistic patients. The positive emotion data collection will be conducted twice to ensure the consistency of the dataset. Before data collection, the headband was worn tightly on the subject head but did not cause any discomfort to the subjects.

Table 1 indicates the characteristics of volunteer demographics in this study. To eliminate the effect of gender and age on machine learning accuracy, we selected the same number of male and female volunteers. We controlled the age of volunteers for the ASD and TD groups.

Table 1. Volunteer Demographics Characteristic

Demographic Characteristic	Component	TD	ASD
Gender	Male	5	5
	Female	5	5
Age	Below 12	0	3
	12-18	2	2
	18-21	5	3
	Above 21	3	2

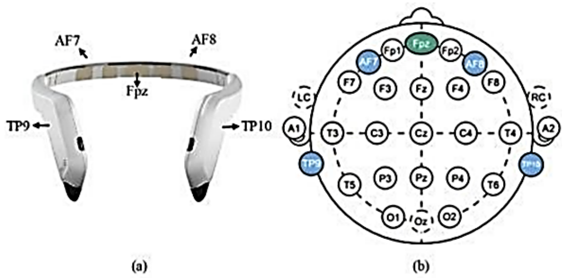

Figure 1. (a) Location of electrodes in MUSE 2 sensor (b) MUSE EEG headset electrodeposition [33]

The subjects were requested to watch a 10-minute favorite video to stimulate positive emotion (joy and happiness) [34] until 500 positive emotion outputs for each subject. If the dataset is not enough 500 positive emotions for the participant, watching another joyful video is necessary. To confirm the accuracy of the data label, an experienced ASD therapist monitored the subject while paying close attention to their feelings. The therapist will cease collecting and classifying EEG data if an emotional change occurs, which also applies to other emotions. After collecting the positive emotion EEG signal data, the subject collected the neutral emotion (bored) [28] signal data after one hour's rest.

Next, the subjects requested to watch 10 minutes of boring or not exciting videos based on the survey form (prevent emotional fluctuation) to collect 500 neutral emotion outputs. After neutral emotion data collection, the above steps were repeated by replacing boring videos with sad or disliked videos based on the survey form, and the negative emotions (fear, anger, sadness, and disgust) [28] in the dataset were produced. The number of EEG signals for each emotion used to train the machine learning will be controlled to precisely 500 signals (the train model will use 400, and others will used for the test model).

2.2 EEG Signal Preprocessing

Before delving into feature extraction and emotion classification, the EEG signal data underwent rigorous preprocessing facilitated by a noise filter to eliminate interference. With MUSE 2 headbands, researchers can access preprocessed or raw EEG signal data. MUSE 2 boasts an impressive output sampling rate 256Hz with a mere 2uV (RMS) noise level. To achieve a pristine signal free from disturbances and optimized for computational efficiency, various techniques, such as employing an onboard driven right leg (DRL) between the Fpz electrode

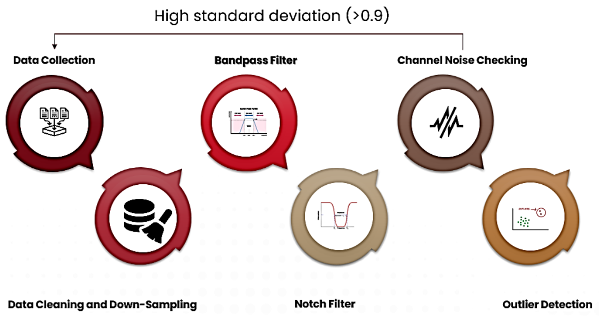

Figure 2. Data Preprocessing Flow for EEG Signal Acquisition

and frontal electrode, utilizing active noise filtering, or employing effective noise cancellation mechanisms, were explored. A feedback circuit (DRL) was meticulously engineered to ensure optimal skin contact with the EEG electrode, consequently minimizing electrode noise. Figure 2 illustrates the meticulous data preprocessing flow it was adopted during the data acquisition phase.

Preprocessing raw EEG signals to eliminate noise comprises several meticulous steps. Initially, BlueMuse imports the raw EEG data from the Muse 2 headset to a laptop buffer, discarding the initial and final 100ms due to the device's mean lag. Subsequently, irrelevant signals such as gyroscope readings, eyeblinks, missing data, or heart rate artifacts were filtered out, and the EEG signals were down-sampled from 256Hz to 128Hz. A Butterworth bandpass filter is applied to refine the data, with cutoff frequencies set at 0.5Hz and 45Hz to remove muscular movements, heartbeat, or eyeblink interference. Additionally, a 50Hz-notch filter eradicates line noise from the power source or battery. Channels were scrutinized for noise, and any channel exhibiting high standard deviation was eliminated. Outlier detection algorithms were deployed to identify and discard signals exceeding predefined thresholds tailored to specific participant groups. Finally, post-preprocessing, only 500 datasets per emotion and participant were retained for subsequent machine learning model training and testing.

2.3 EEG Signal Feature Extraction

The noise-free signal was acquired after the data preprocessing stage. Brainwave speed was measured in Hertz (cycles per second), and they were divided into bands delineating slow, moderate, and fast waves. There are five EEG bands, which are delta (0–4 Hz), theta (4–8 Hz), alpha (8– 12 Hz), beta (12–30 Hz), and gamma (30-42 Hz), but these band definitions will differ between research [28, 29, 30]. These frequencies represent different functions and states of the brain. Other states have specific cortical topography, processes, and physiology [31]. Several feature extraction methods were used to extract essential features, such as t-test, Chi-square, principal component analysis (PCA), and ReliefF.

2.3.1 T-Test

A t-test is one of the standard statistical analysis methods used to identify the differences between two data sets. The t-test is also a hypothesis test that differentiates whether a set of scores is from a different population. There are three types of t-tests: the samples t-test, paired samples t-test, and one-sample t-test. In this study, a two-sample t-test was applied. The two sample T-value was represented by t, and the formula is as follows:

$$\boldsymbol{t} = \frac{\boldsymbol{\mu 1 - \mu 2 - \Delta}}{\sqrt{\frac{\boldsymbol{\delta 1}}{\boldsymbol{n1}} + \frac{\boldsymbol{\delta 2}}{\boldsymbol{n2}}}} \quad (1)$$

where μ1 and μ2 are the two samples' mean, respectively, δ1 and δ2 are the standard deviations for the two samples, and n1 and n2 are the two samples' sizes, respectively. Δ is the hypothesis difference between population means (hypothesis difference = 0 if testing for a population equal mean) [33, 34].

2.3.2 Principal Component Analysis

Principal Component Analysis, or PCA, is a dimensionality-reduction approach for reducing the dimensionality of big data sets by converting an extensive collection of variables into a smaller set that maintains most of the information in the more comprehensive set [41].

PCA was based on this mathematical formula: three m x n matrices indicated by the letters y, x, and p.

$$y = px \quad (2)$$

where y represents the output matrix, x represents the input matrix, and p represents the projection matrix, each column representing a main component.

$$\text{Px} = \begin{pmatrix} p1x1 & p1x2 & \dots & p1xn \\ p2x1 & p2x2 & \dots & p2xn \\ . & . & . & . \\ pmx1 & pmx2 & \dots & pmxn \end{pmatrix} \quad (3)$$

This is the matric version of the equation. [35]. X represents columns of P projected to original data, and PmXn represents the inner product of standard Euclidean (m is row number and n is column number).

2.3.3 ReliefF

Relief algorithms are general and successful attribute estimators. They can detect conditional dependencies between attributes and provide a unified view of the attribute estimation in regression and classification. There were three types of relief algorithms: the basic relief algorithm [36], ReliefF [37], and RReliefF [38]. The basic Relief algorithm was used for binary classification, and the RReliefF algorithm was created by adapting RReliefF to continuous class (regression) issues. In this study, ReliefF was used to classify the emotions of the ASD group since ReliefF was an extension of Relief, which dealt with multiclass problems.

2.3.4 Chi-Square

The Chi-square statistic is a test that evaluates how well a model matches actual data. A chi-square statistic requires random, raw, mutually exclusive data from independent variables and a vast enough sample. The Chi-Square test of independence was used to see if two category (nominal) variables have a significant connection. The Chi-Square test of independence was used to see if two category (nominal) variables have a significant connection [39]. The following equation explains the working principle of the Chi-square:

$$\chi c2 = \sum_{n=1}^{\infty} \left(\frac{(On - En)^2}{En} \right) \quad (4)$$

where c is the degree of freedom, O is the observed value, χc2 is the P-value, n is the data index, and E is the expected value. A higher X2 implies a stronger association between a feature variable and the target classes in this study.

2.4 Emotion Classification

After EEG signal feature extraction, the dataset was saved as an Excel file for further analysis using Python. The unwanted reading will be removed. The dataset is labeled based on the current emotion. In this experiment, 20 parameters were collected, namely Alpha waves (TP9, TP10, AF7, and AF8), Beta waves (TP9, TP10, AF7, and AF8), Gamma waves (TP9, TP10, AF7, and AF8), Theta wave (TP9, TP10, AF7, and AF8), Delta wave (TP8, TP9, AF7, and AF8). Those features will pass into the machine learning module to classify the emotions of the ASD group. The machine learning module applied to classify the emotion is K-nearest Neighbor (KNN), Multinomial Logistic Regression (MLR), Naïve Bayes (NB), Random Tree (RT), Random Forest (RF), and Support Vector Machine (SVM). The machine learning algorithm will create a function to describe the relationship between input and output; thus, the system will generate the prediction through the function. The suitable algorithm and parameter need to be determined so the machine learning function won't create overfit or underfit output, which will generate inaccurate predictions.

2.5 Model Validation

In machine learning, evaluating the accuracy of the trained model was known as model validation with test data from the original dataset [40]. Some validation methods had been proposed after preparing sufficient testing set data for data validation, such as K-fold cross-validation, stratified sampling, and random sampling. In this study, K-fold cross-validation was used to identify the accuracy of the emotion classification model.

2.5.1 K-Fold Cross Validation

Rotation estimation or cross-validation is a technique to validate the machine learning model by reserving a percentage of data from the original dataset (split data) and using the reserved data to evaluate the trained model's accuracy [41]. The cross-validation function compares the accuracy or performance of different trained models. There are three main types of cross-validation techniques: K-fold cross-validation, bootstrapping, and leave-one-out cross-validation. Meanwhile, K-fold cross-validation is widespread and is usually used for most research.

The central concept of K-fold cross-validation is randomly separating the original dataset into k number of equal-size instance groups (folds). One-fold was left out as a training set, which was used to train the machine learning model, while the other fold will be used to test or evaluate machine learning model performance. Repeat this process k times until all folds are used as the test or train datasets. Finally, all folds of the dataset performance measures are average to evaluate the algorithm's ability to solve the problem.

3. RESULT AND DISCUSSION

The t-test approach decreased the number of characteristics from 20 to 13. The features from the data shown to be statistically distinct were then subjected to the feature selection approach (RELIEF, PCA, and Chi-square). Table 2 provides an overview of the features chosen for the ASD group's emotion classification module, and Table 3 indicates the TD group emotion classification with an optimized feature number.

Selecting EEG sensors and measurement techniques for emotional analysis in ASD is intricate, particularly in studies involving multiple variables. Given the complexity of data analysis, diverse options are available regarding the physical principles governing signal recording and physiological parameters. These options offer substantial avenues for evaluating emotional classification in ASD patients [32].

Based on Table 5, the overall accuracy of the TD group emotion classification model is higher than that of the ASD group. The highest accuracy of the TD group emotion classification model is Random Forest with Chi-Square as feature selection. The high accuracy is due to the TD group's more significant and accessible emotions. The TD group has fewer emotional fluctuations than the ASD group. Therefore, the accuracy of the TD group is higher than that of the ASD group.

The availability of various measurement technology options, especially EEG sensor technology, created more opportunities for analyzing gamma and beta bands. However, noticeable methodological challenges were encountered during emotional recognition, which could be attributed to the dataset's ununified conception [33], and it was solved by adjusting the control group sizes, experimental time, and compositions based on the data samples. Analysis techniques and signal processing are also crucial in determining the sensors and methods of measurement [38].

The EEG data were obtained under relaxed conditions with eyes either closed or opened during object recognition or sleep through video or audio tasks [39]. Though the findings are variable, the following generalizations can be inferred: emotional connectivity in ASD patients is due to long-range connections in the alpha-band between the amygdala and the frontal lobe regions [42].

Therefore, research findings support the under-connectivity theory of autism spectrum disorders. The research's functional connectivity established a consistently increased short-range connectivity in the alpha band and long-range connectivity in the beta band [40]. These findings show the potential and reasonable utility of integrating functional connectivity measures for ASD emotional classification.

Table 2. Optimized features number for ASD group emotion Classification

Module	Original	ReliefF	Chi-Square	T-Test	PCA
Features Number	20	16	15	13	11

Table 3. Optimized features number for TD group emotion Classification

Module	Original	ReliefF	Chi-Square	T-Test	PCA
Features Number	20	11	9	10	7

Table 4. Model accuracy of the different models on different emotion classification modules for the ASD group

Feature Selection	KNN	MLR	NB	RT	RF	SVM
Original	62.8	59.5	40.4	60.2	66.8	66.4
Chi-Square	63.0	57.9	43.3	59.7	66.7	66.3
T-Test	69.1	60.4	36.2	66.4	71.2	74.1
ReliefF	60.9	58.4	45.2	59.7	65.8	64.6
PCA	63.0	55.2	51.3	55.7	63.6	65.3

Table 5. Model accuracy of the different models on different emotion classification modules for the TD group

Feature Selection	KNN	MLR	NB	RT	RF	SVM
Original	86.3	52.3	50.4	86.4	88.8	86.6
Chi-Square	91.4	63.4	44.8	86.7	89.8	77.8
T-Test	86.3	47.9	42.0	86.2	88.0	77.6
ReliefF	86.3	58.2	42.0	86.3	89.0	87.6
PCA	86.3	53.8	50.9	84.3	87.5	86.0

3.1 Cross-Validation

Fivefold cross-validation was utilized in this study to determine the efficacy of the emotion classification model for the ASD group. In general, the training data and testing data will be split into K pieces. In this study, we set K to 5, splitting the data into five folds after all participants' data was merged. All participants' training data was analyzed, and the accuracy of the emotion classification model was calculated using this method. With 5-fold cross-validation training and testing data for the emotion recognition dataset, the results of the average classification accuracy for both models are shown in Table 4 and Table 5.

It is clear from the results that the SVM model outperforms the other classification models in terms of classification accuracy for training-testing data with an 80-20 split. Apart from the classification model using NB, it is also evident from the results that the feature extraction method using the T-test will yield the best results, demonstrating that removing the undesirable features from the dataset facilitates the selection of the best features and boosts accuracy.

The SVM model using t-test feature extraction for 5-fold cross-validation samples produced an astounding 74.1% classification accuracy with an average of 13 features for the EEG dataset. If adequate training data were provided, the t-test would have good adaption-generating capabilities and could choose the ideal number of features. The outcome supports the need for appropriate training data when selecting the best features from the dataset.

Confusion Matrix				
TARGET / OUTPUT	Positive	Neutral	Negative	SUM
Positive	578 19.27%	128 4.27%	314 10.47%	1020 56.67% 43.33%
Neutral	263 8.77%	811 27.03%	225 7.50%	1299 62.43% 37.57%
Negative	159 5.30%	61 2.03%	461 15.37%	681 67.69% 32.31%
SUM	1000 57.80% 42.20%	1000 81.10% 18.90%	1000 46.10% 53.90%	1850 / 3000 61.67% 38.33%

Figure 3. Confusion matrix for SVM classifier with all features

3.2 Confusion Matrix

A confusion matrix was employed to assess each class's sensitivity to the impact of EEG signals on the accuracy of emotion classifiers. Figure 3 and Figure 4 represent the result of the confusion matrix of SVM with all features and t-test feature selection, respectively. As per Figure 3, the probability of the SVM model misclassifying positive and negative emotions is higher than neutral. Meanwhile, Figure 4 shows that the likelihood of misclassifying negative emotions is lower than positive and neutral ones.

3.3 Accuracy Verification Indexes

The accuracy verification index employed in this investigation was Macro F1. The macro version of the F1-score accuracy verification index, utilized for multiclass and binary classification, is called macro F1. The recall is the ratio of correctly retrieved samples to samples that were supposed to be retrieved.

$$Recall = \frac{TP}{(TP+FN)} \tag{5}$$

Of all the instances the model obtained, precision is the proportion of relevant occurrences.

$$Precision = \frac{TP}{(TP+FP)} \tag{6}$$

The F-score is a complete evaluation measure that considers both recall and precision. F-score:

$$F - score = (1+\beta^2) * \frac{Precision * Recall}{\beta^2 * (Precision * Recall)} \tag{7}$$

To maintain a balance between recall and precision, the value of β was set to 1, and the F1-score metric was adopted. Table 6 indicates the precision, recall, and F1-score for the ASD emotion classification model using the ASD group test dataset in this study.

Confusion Matrix				
TARGET / OUTPUT	Positive	Neutral	Negative	SUM
Positive	731 24.37%	172 5.73%	95 3.17%	998 73.25% 26.75%
Neutral	157 5.23%	573 19.10%	115 3.83%	845 67.81% 32.19%
Negative	112 3.73%	255 8.50%	790 26.33%	1157 68.28% 31.72%
SUM	1000 73.10% 26.90%	1000 57.30% 42.70%	1000 79.00% 21.00%	2094 / 3000 69.80% 30.20%

Figure 4. Confusion matrix for SVM classifier with t-test

RF has the highest recall of these emotion classifiers, with a recall of 0.701, indicating a higher percentage of accurate prediction. MLR, on the other hand, has the lowest recall (0.582), which suggests that the retrieval is only partially correct.

SVM has the greatest F1-score (0.695), whereas MLR has the lowest (0.582). The final metric, the F1 score, combines recall and accuracy; a high F1 score indicates minimal false positives and false negatives. The model is a complete failure with a score of 0, while the perfect F1 score is 1.

Table 7 indicates the recall, precision, and F1 of TD group emotion classification with the ASD group test dataset. Overall evaluation performance for the ASD test dataset is less than 50%, lower than the ASD emotion classification model. Thus, the TD group's emotion classification model was not used for ASD group emotion prediction.

Performance measures with greater percentage values indicate a better model. The performance measures climb as more picked samples were successfully identified. In this study, we found high F1 scores and accuracy, which can inform others about the optimal algorithms for testing ASD people.

Accurate detection of emotional behavior is pivotal in diagnosing autism spectrum disorders (ASD). Despite its importance, limited techniques hinder scientific progress in emotion classification. Consequently, the healthcare sector, particularly in specialized care like autism, must integrate technological solutions like wireless EEG monitoring devices for improved ASD diagnosis and treatment. [38]. The use of wireless EEG monitoring devices in the classification of emotions has proven to be an effective way of boosting logical decision-making, human interaction, and perception and improving the human intelligence of special-care patients. The research has also established that integrating EEG in emotion recognition and classification has positively impacted the development of wireless consumer-grade wearables systems [32].

Table 6. Precision, recall, and F1 of the different emotion classification modules (ASD module, t-test) for the ASD group test dataset

Classifier	Precision	Recall	F1
KNN	0.687	0.686	0.670
MLR	0.582	0.618	0.582
NB	0.585	0.616	0.600
RT	0.660	0.670	0.656
RF	0.705	0.701	0.684
SVM	0.697	0.698	0.695

Table 7. Precision, recall, and F1 of the different emotion classification modules (TD module, Chi-Square) for ASD group test dataset

Classifier	Precision	Recall	F1
KNN	0.37	0.477	0.371
MLR	0.379	0.478	0.389
NB	0.428	0.400	0.402
RT	0.385	0.422	0.395
RF	0.388	0.489	0.378
SVM	0.409	0.494	0.384

SVM was commonly used for autism data analysis because of its versatility in handling nonlinear data. The statistics show that the SVM's accuracy varied from 64.6 to 74.1 percent. Several approaches can be used to improve accuracy. The SVM method was used in prior work [33] to increase the patients' categorization accuracy using the entire Autism Brain Imaging Data Exchange (ABIDE). The study includes gathering information from 501 autistic participants. The top 1000 attributes from the initial functional connectivity features were selected using the SVM method. Finally, the training was done with the help of a stacked sparse autoencoder with two hidden layers for extracting the high-level latent data and complicated attributes from the initial features. The optimal features were fed into the classifier. Because of its ability to deal with nonlinear data, SVM was widely utilized for analyzing autism-related data.

However, SVM can be disadvantageous because of the difficulty of choosing the suitable kernel function. In the case of nonlinear data, selecting the appropriate kernel function can be complex. Many support vectors need to be generated if the dimension of the cardinals increases. As a result, the training speed also decreases significantly. The requirement for extensive memory is another disadvantage of SVM. Algorithm complexity is also high for this algorithm. The users require substantial memory to store information regarding the support vectors. The number increases abruptly with the training data set.

This study underscores the efficacy of the t-test in eliminating extraneous features and selecting traits exhibiting substantial differences. Utilizing the t-test was advocated to prune redundant features and enhance the accuracy of the machine learning model employed for emotion classification within the ASD group.

In a previous study [43], the accuracy of the emotion classification for the typically developing (TD) group provided 82.27% for eight different emotion states, using KNN as a classifier. The accuracy of the emotion classifier for the TD group was much higher than that of the ASD group because the ASD group had difficulty performing facial expressions. Thus, increasing the number of sampling data for each ASD participant will improve the accuracy of the emotion classification model.

Table 8. Comparison with the related works

Method	Stimulus	No. Volunteer	Emotion	Accuracy
Clinical EEG [46]	IAPS	21 (TD)	calm, scared, sad, happy	58% SVM 55% KNN
Clinical EEG [47]	video	25 (TD)	positive and negative	57% QDA 62% KNN
Clinical EEG [48]	video	32 (TD)	11 different emotions	82% SVM 74% MLP 58% KNN 76% MMC
Muse 2[49]	music	27 (TD)	happy, angry, sad, relax	81% MLP 79% RF
Clinical EEG [45]	video	99 (ASD + TD)	positive and negative	98.6% LSVM
Clinical EEG [44]	video	12(ASD)	positive and negative	85.5% LSVM
Clinical EEG [50]	video	12 (ASD)	positive and negative	98.5% KNN
Our Work	video	10(ASD)	Positive, neutral, and negative	74.1% SVM (t-test)

Table 8 summarises the emotion classification results for different emotions in the ASD group. Most previous works focus on either the TD group with wireless EEG monitoring devices or the ASD group with clinical EEG monitoring devices. To prior studies, no previous studies have focused on ASD group emotion classification utilizing wireless dry EEG monitoring devices. This study aims to establish frameworks and guidelines for ASD emotion classification through wireless dry EEG monitor devices.

Clinical EEG monitoring devices are commonly regarded as offering superior accuracy compared to wireless dry EEG monitoring devices. In a seminal study [44], the author utilized a dataset consisting of 12 ASD EEG recordings and 87 TD group EEG recordings to train the Lagrange Support Vector Machine (LSVM). The findings revealed an exceptional accuracy exceeding 98.6% for classifying positive and negative emotions.

On the other hand, this study's accuracy (74.1%) is close to that of a previous study [53], but this study was conducted on the TD group. The low accuracy is due to the data label's accuracy for the training dataset. However, the accuracy of the TD group in this study is higher than that of the study [53], which used Chi-Square to remove unnecessary features.

To further improve this study's results, electrooculogram, electrocardiogram, and electromyography should be considered features of the emotion classification model.

4. CONCLUSION

The neurophysiological analyses conducted in this study revealed a significant correlation between human emotions and EEG signals, particularly emphasizing the involvement of key brain regions such as the frontal lobe and the amygdala in emotional processing. Notably, the study highlighted a predominance of emotional activations within the frontal scalp compared to other brain regions, including the occipital, temporal, and parietal lobes. Furthermore, the research introduced a novel approach to enhance the accuracy of emotion classification models for individuals with ASD by extracting pertinent features. Utilizing the T-test methodology, critical features were identified and incorporated into the emotion classification model, resulting in a notable improvement in accuracy from 66.4% to 74.1% with SVM. Among the array of machine learning methods explored, SVM and RF emerged as the top performers for emotion classification within the ASD group.

ACKNOWLEDGMENT

The authors would like to thank the Kiwanis Circle Love and REACH Segamat for providing support during the data collection process. This work has been supported by Universiti Teknologi Malaysia through Hi-Tech (F4) Q.J130000.4623.00Q15 grant in the project F4 3.3: Edge Artificial Intelligence for Suspicious Human Activity Recognition.

REFERENCES

[1] P. Association. "Diagnostic and statistical manual of mental disorders, 5th ed. Arlington: American Psychiatric Association", 2013.

[2] P. Association. "Autism Spectrum Disorder. Diagnostic and Statistical Manual of Mental Disorders. Washington: American Psychiatric Association", 1994.

[3] L. Kanner., "Autistic disturbances of affective contact. Acta Paedopsychiatrica," Vol. 35, pp. 100-136, 1968

[4] M. O'Reilly, A. Sorrels, S. Gainey, et al., "Naturalistic approaches to social skills training and development. Children and Youth with Autism Spectrum Disorder," pp. 90-100, 2014

[5] G. Dawson, S. J. Webb, G. D. Scheellenberg, et al. "Defining the broader phenotype of autism: genetic, brain, and behavioral perspectives," Dev Psychopathol, vol. 14, pp. 581-611, 2002

[6] S. N. Avery, S. Heckers, J. U. Blackford, R. M. VanDerKlok, "Impaired face recognition is associated with social inhibition," Psychiatry research. Vol. 236: pp. 53-57, 2016.

[7] Deruelle, C. Rondan, X. Salle-Callemiche, D. Bastard-Rosset, et al. "Attention to low- and high-spatial frequencies in categorizing facial identities, emotions and gender in autistic children," Brain and cognition. Vol. 66, pp. 115-123. 2008.

[8] N. William. Core challenges of autism, "Sensory aspects of autism," Autizm i narusheniya razvitiya. Vol. 14: pp. 42-48. 2016.

[9] Ehrenreich JT, Fairholme CP, Buzzella BA, Ellard KK, Barlow DH. "The Role of Emotion in Psychological Therapy," Clin Psychol (New York). Vol. 14: pp. 422-428. 2007.

[10] Zhang, H.; Luo, S.; Yoshie, O. "Facial expression recognition by analyzing features of conceptual regions," In Proceedings of the 2013 IEEE/ACIS 12th International Conference on Computer and Information Science (ICIS), Niigata, Japan. Pp. 529–534.- 2013.

[11] Al Machot, F., Elmachot, A., Ali, M., Al Machot, E., & Kyamakya, K., "A Deep- Learning Model for Subject-Independent Human Emotion Recognition Using Electrodermal Activity Sensors," Sensors (Basel, Switzerland), vol. 19, pp. 1659, 2019

[12] Kerkeni, Leila & Serrestou, Youssef & Raoof, Kosai & Cléder, Catherine & Mahjoub, Mohamed & Mbarki, Mohamed, "Automatic Speech Emotion Recognition Using Machine Learning," IntechOpen. 10.5772/intechopen.84856, 2019.

[13] M. Soleymani, M. Pantic and T. Pun., "Multimodal Emotion Recognition in Response to Videos." IEEE Transactions on Affective Computing, Vol. 3, pp. 211-223, 2012

[14] H. Ranganathan, S. Chakraborty and S. Panchanathan. "Multimodal emotion recognition using deep learning architectures," 2016 IEEE Winter Conference on Applications of Computer Vision (WACV), pp. 1-9, 2016.

[15] Y. Wang, T. M. Sokhadze, A. S. El-Baz, X. Li. "Relative power of specific EEG bands and their ratios during neurofeedback training in children with autism spectrum disorder. "Front Hum Neurosci, vol. 9: pp.1-11, 2016.

[16] P. L. A. Schoenberg, A. David. "Biofeedback for psychiatric disorders: a systematic review." Appl Psychophysiol Biofeedback. vol. 39, pp. 109-135, 2014.

[17] Hinrichs, H., Scholz, M., Baum, A.K. et al. "Comparison between a wireless dry electrode EEG system with a conventional wired wet electrode EEG system for clinical applications." Sci Rep. vol. 10, pp. 5218, 2020.

[18] Choppin. "A. EEG-Based Human Interface for Disabled Individuals: Emotion Expression with Neural Networks Submitted for the Master Degree, Emotion," 2000.

[19] Ramirez, R., M. Palencia-Lefler, S. Giraldo and Z. Vamvakousis. "Musical neurofeedback for treating depression in elderly people," Frontiers in Neuroscience. Vol. 9: pp. 354, 2015.

[20] F. Duan, K. Watanabe, M.Kikuchi, et al. "Detection of atypical network development patterns in children with autism spectrum disorder using magnetoencephalography." PLoS One, vol. 12, pp.1-24, 2017.

[21] Fedotchev, S. B. Parin, S. Polevaia, S. Velikova. "Brain-computer interface and neurofeedback technologies: current state, problems and clinical prospects (review)." Sovremennye tehnologi v medicine. vol. 9, pp. 175-184, 2017.

[22] Gurau, C. Newton, W. Bosl. "How useful is electroencephalography in diagnosis of autism spectrum disorders and the delineation of subtypes: A systematic review," Front Psychiatry. Vol. 8, pp. 12-24, 2017.

[23] Górecka, J., & Makiewicz, P. "The Dependence of Electrode Impedance on the Number of Performed EEG Examinations." Sensors (Basel, Switzerland). vol. 19, pp. 2608, 2019.
[24] Fiedler, P. et al. "Multipin Electrode Cap System for Dry Electroencephalography." Brain Topogr, vol. 28, pp. 647–656, 2015.
[25] Hinrichs, H., Scholz, M., Baum, A.K. et al. "Comparison between a wireless dry electrode EEG system with a conventional wired wet electrode EEG system for clinical applications." Sci Rep. vol. 10, pp. 5218, 2020.
[26] Erikson EH. (1963). Childhood and Society. (2nd ed.). New York: Norton.
[27] N. Zhuang, Y. Zeng et al, "Investigating Patterns for Self-Induced Emotion Recognition from EEG Signals", Sensoors, vol. 18, 841-863, 2018.
[28] M. P. Eladhari, M. Sellers. "Good moods: outlook, affect and mood in dynemotion and the mind module." The Journal of the Canadian Game Studies Association. Vol. 3, pp.1-8. 2009.
[29] Kaur, B.; Singh, D.; Roy, P.P. "EEG-based emotion classification mechanism in BCI." Procedia Comput. Sci. vol. 132, pp. 752–758, 2018.
[30] Sawangjai, P.; Hompoonsup, S.; Leelaarporn, P.; Kongwudhikunakorn, S.; Wilaiprasitporn, T. "Consumer-grade EEG Measuring Sensors as Research Tools: A Review." IEEE Sens. J., vol. 20, pp.3996–4024, 2019.
[31] Kawala-Janik, A.; Pelc, M.; Podpora, M. "Method for EEG signals pattern recognition in embedded systems," Elektron. Elektrotechnika. vol. 21, pp. 3–9, 2015
[32] Cajochen, C., Foy, R., and Dijk, D.-J. "Frontal predominance of a relative increase in sleep delta and theta EEG activity after sleep loss in humans." Sleep Res. Online. vol. 2, pp. 65–69, 1999
[33] D'Arcey, J. T. and J. Trevor. "Assessing the validity of FaceReader using facial EMG," Master's thesis, Faculty of California State University, Chico. 2003.
[34] Isaacowitz, D. M., C. E. Lo¨ckenhoff, R. D. Lane, R. Wright, L. Sechrest, R. Riedel and P. T. Costa. "Age differences in recognition of emotion in lexical stimuli and facial expressions," Psychology and Aging. vol. 22, pp. 147–159, 2007.
[35] M. Didier, M.K. Joseph, N. Marcel. "Applying principal component analysis for qualification and quantification of the contribution of key foreign exchange earners in Rwanda (1999-2013)." International Journal of Social Science and Humanities Research, vol. 4, pp. 714-723, 2016
[36] K. Kira, L.A. Rendell. "The feature selection problem: Traditional methods and a new algorithm." The Tenth National Conference on Artificial Intelligence (AAAI- 92), San Jose, California, 1992.
[37] N. Spolaôr, E. A. Cherman, M. C. Monard and H. D. Lee. "ReliefF for Multi-label Feature Selection." Brazilian Conference on Intelligent Systems. Vol. 2013, pp. 6-11, 2013.
[38] Robnik-Šikonja, M., Kononenko, I. "Theoretical and Empirical Analysis of ReliefF and RReliefF." Machine Learning, vol. 53, pp.23–69, 2003
[39] McHugh, Mary L. "The chi-square test of independence." Biochemia medica. Vol. 23, pp. 143-152, 2013
[40] Ferdinandy B, Gerencsér L, Corrieri L, Perez P, Újváry D, et al. "Challenges of machine learning model validation using correlated behaviour data: Evaluation of cross-validation strategies and accuracy measures." PLOS ONE, vol. 15, pp. 1-14. 2020.
[41] I.H. Witten, E. Frank, M.A. Hall, "Data mining: Practical machine learning tools and techniques", Morgan Kaufmann, 2011.
[42] I.H. Witten, E. Frank, M.A. Hall, "Data mining: Practical machine learning tools and techniques", Morgan Kaufmann, 2011.
[43] P.Lahane, A. K. Sabgaiah. "An Approach to EEG Based Emotion Recognition and Classification Using Kernel Density Estimation." Procedia Computer Science. vol. 48, pp. 574-581, 2015.
[44] Aslam, A. R., Hafeez, N., Heidari, H., and Altaf, M. A. B. "An 8.62 μ w processor for autism spectrum disorder classification using shallow neural network" 2021 IEEE 3rd International Conference on Artificial Intelligence Circuits and Systems (AICAS) (Washington DC: IEEE) pp.1-4, 2021.
[45] A. R. Aslam, N. Hafeez, H. Heidari and M. A. B. Altaf, "Channels and Features Identification: A Review and a Machine-Learning Based Model with Large Scale Feature Extraction for Emotions and ASD Classification", Front. Neurosci, vol. 16, pp. 1 – 15, 2022.
[46] Mehmood, R. M. and H. J. Lee, "A novel feature extraction method based on late positive potential for emotion recognition in human brain signal patterns," Computers and Electrical Engineering, 2016.
[47] Sorinas, J., Ferrández, J. M., & Fernandez, E. "Brain and Body Emotional Responses: Multimodal Approximation for Valence Classification." Sensors (Basel, Switzerland), vol. 20, pp. 313. 2012.
[48] Verma, G.K.; Tiwary, U.S. "Multimodal fusion framework: A multiresolution approach for emotion classification and recognition from physiological signals." NeuroImage, vol. 102, pp. 162–172, 2014.
[49] R. Zainab and M.Majid, "Emotion Recognition based on EEG Signals in Response to Bilingual Music Tracks." The International Arab Journal of Information Technology.vol.18, pp 286-296, 2021
[50] Liu, S., Wang, X., Zhao, L., Li, B., Hu, W., Yu, J., et al. "3dcann: a spatio-temporal convolution attention neural network for eeg emotion recognition.", IEEE J. Biomed. Health Inform, vol.26, pp5321-5331, 2021.