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Emotion Recognition using Galvanic Skin Response (GSR) Signal

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ABSTRACT

Physiological signals play a vital role in emotion recognition as they are not controllable and are of immediate response type. The primary purpose of this work is to acquire skin conductance of GSR by performing GSR signal classification for emotion recognition using various classifiers. Machine learning applications penetrate more spheres of everyday life. Recent studies show promising results in analyzing other physiological signals using machine learning to access emotional states. Commonly, specific emotions are invoked by playing compelling videos or sounds. However, there is no canonical way for emotional state interpretation. The primary materials are GSR data signals collected from ASCERTAIN database and MATLAB software. The affective arousal seven-point emotional scale was obtained from the classified GSR signals implemented using machine learning algorithms. Features and class labels can be imported into the Classification Learner application in MATLAB software to train and test various classifiers. A comparison of GSR signal classification of the different classifiers has shown that the highest accuracy was achieved using k-nearest neighbours (KNN) and Ensemble classifiers with 97.9% emotion detection. The advantage of this work shows the importance of features and class label selection in emotion recognition tasks. Moreover, the dataset obtained must be suitable for machine learning algorithms. Acquired results may help select proper GSR signals with emotional labels for further dataset pre-processing and feature extraction.

1. Introduction

In reaction to physical and emotional stimuli, galvanic skin response (GSR) changes it electrical properties that increases the subject's level of excitability [20]. Signals are a measure of sweat gland function and can be used to determine autonomic responses. The response comes in the form of an increase in electrical conductance as the resistance of the palm or sole of the foot decreases. Response appears 2 seconds after receiving a stimulus such as a pin puncture or risk of injury, forms after 2 to 10 seconds, and begins to fade at the same rate [14]. Thus, GSR is a basic and sensitive indicator of peripheral sympathetic nervous system activity and autonomic changes.

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A review on GSR discloses three major theories that propose to explain the phenomenon [15]. (i) Muscle activity: GSR is a direct representation of muscle bioelectrical changes. The results show that there is a non-causal relationship; (ii) Vascular changes: GSR is an electrical activity that occurs during vasodilation or vasoconstriction. But in this case, the data is compelling that prioritize correlation over causality; (iii) Secretory changes: GSR stands for the sweat glands' pre-secretory electrical activity. The mechanics are still unknown, but the data is given to support this explanation as the best among them.

Emotion recognition is the study of identifying six universal expressions, including anger, pleasure, fear, happiness, sorrow, and surprise, using various computer science approaches. Emotions reveal a person's mental condition through negligent acts, which may or may not be paralinguistic. A person's feelings are identified through behavioural traits such as speech, handwriting, facial expressions, brain impulses, and heart signals. Not only are behavioural features used to identify a person, but they also aid in understanding emotions. They are sometimes referred to as soft biometrics [17]. Soft biometrics can be categorised as physical, behavioural, and human adhering characteristics. Height, weight, skin colour, and eye colour are physical features. While voice, stride, and keystroke are examples of behavioural traits. Soft biometrics facilitate the semantic interpretation of a person's thoughts, emotions, behaviours, and physical appearance to identify emotions. Aside from emotion detection, additional characteristics such as valence, polarity, and arousal play essential roles in determining one's mental state. Sentimental Analysis, as defined by Kaur and Kulkarni, [16], is the mapping of the brain utilising valence, polarity, arousal, and emotion identification.

This study's main contribution is automatically identifying emotion based on information in human GSR signals. The identification was only performed using the GSR signal in this study. Whereas many reported works were based on multiple physiological signals such as galvanic skin response (GSR) with heart rate (HR), skin temperature (ST), respiratory sensor, blood pressure (BP), monitor pulse oximetry, respiratory rate, and electrocardiography (ECG) [1,2,5,7-9]. Multiple applications to human life have been demonstrated, including patient-doctor interactions in diseases and intellectual disabilities like schizophrenia and autism [23]. GSR signal for emotion detection can be achieved using various time domain signal features like the root mean square, shape factor, peak value, crest factor, clearance factor, and impulse factor of the filtered signals. Time domain features are extracted from raw GSR signals, making them easy to implement [31]. The easy implementation is a significant advantage of the features as no or little data are lost before inspection of the signal [19]. In the time domain, the signal or function's value is known for all real numbers in the case of continuous time or at various separate instants in the case of discrete time [32]. GSR was first associated with stress, the potential approach to evaluating stress emotion. Current research shows a new way to classify stress levels based on physiological signals during actual driving work using a single signal galvanic skin response (GSR). The classifier's effectiveness and quality are tested, which achieved high accuracy level [13]. It has been found to help recognize different types of emotions in real-life situations. Thus, in this research, various time domain features will be utilized in emotion identification using multiple classifiers. There will be an emphasis on the findings of this study and the prospects for future research in this area.

The rest of the paper is organized as follows. The related works are exposed in Section 2. Section 3 presents the materials used and the methodology to accomplish the objectives. The results, analysis, and discussion data are discussed in Section 4. Finally, Section 5 is devoted to the conclusion and future work.

2. Related Works

Studies have developed heart rate (HR), galvanic skin response (GSR), skin temperature (ST), respiratory sensor, blood pressure (BP), electrodermal activity (EDA), monitor pulse oximetry, respiratory rate, and electrocardiography (ECG) to detect people's emotional states [1-13]. Also, these signals act as an indicator of a person's response to stress. From all the signals mentioned, this study focused on using galvanic skin response (GSR) for emotion recognition.

The experiment design by authors in each paper have been conducted differently which produced various method of emotion detection. The stress task was designed in Kontaxis *et al*., [4] and Lutin *et al*., [11] which is Arithmetic Test. Methods used in Cantara *et al*., [1], Chauhan *et al*., [5], Egilmez *et al*., [7], Rodríguez-Arce *et al*., [8], Ayata *et al*., [10], Navea *et al*., [12], Memar *et al*., [13] were using Stroop Test, Daily Routine, 9 mental task activities, STAI self-report Questionnaire, Biosensor, Mobile Communication (Android Application), Healey and Picard during a real-world driving respectively. Some studies used tense and calm conditions [2], social expose, stressful event recall, cognitive load, stressful videos [3], SCWT, light physical exercise [6], email interruption, time pressure [9]. The study by Kontaxis *et al*., [4] used the highest number of samples on an experiment design which is 80 subjects meanwhile the lowest number of samples was produced by Memar *et al*., [13] which is 8 subjects. The number of samples for other studies ranged between 9 to 32 subjects.

Next, the proposed techniques used in emotion detection consist of two critical components: features and classifier. Both studies Cantara *et al*., [1] and Setiawan *et al*., [2] used a Fuzzy Logic algorithm as the features with an adaptive neuro-fuzzy interface system (AVFIS) and the C# programming language as the classifier. Various feature extraction methods were used by researchers such as minimum redundancy maximum relevance (MRMR) selection algorithm [3], wavelet cross-bispectrum (WCB) and cardiorespiratory [4], zero crossing method and discrete wavelet transform [5], correlation-based feature selection (CFS), information gain ratio-based feature selection and principal component analysis (PCA) as reduction technique of features [6], event based (EB) and minute based (MB) [7], the MATLAB software was used to process each signal and extract features [8], Welch's algorithm and Periodogram [9], Time domain, wavelet, and Empirical Mode Decomposition [10], Trough peak, decomposition-based, frequency, and time-frequency features. Three different applications have been used in the decomposition analysis: Ledalab, cvxEDA, and sparsEDA [11].

Moreover, most of the studies use the similar classifier which is Support Vector Machine (SVM) [3-7]. One of the techniques used for feature extraction is pre-processing and thresholding on eSense GSR application. The classification GSR data processing is performed by using GSR App [12] but the study did not mention the validation type. Besides, the validation type of statistical style is not applicable because it used the ANOVA method with feature extraction Skin Conductance Response (SCR) [13]. Studies such as Cantara *et al*., [1] and Setiawan *et al*., [2] have applied different methods to validate the emotion recognition techniques used in respective studies. For example, in Cantara *et al*., [1], the authors used the Training Test Split with the ratio 3:2 contained 60% of train the algorithm and 40% of test reliability algorithm, meanwhile in Setiawan *et al*., [2] using fuzzy logic or system. The rest of these studies [3-11] have used the cross-validation technique consisting of zero crossing, 3-fold, 10-fold, and 20-fold respectively.

Furthermore, the highest accuracy was 95.83% achieved by Memar *et al*., [13], followed by 92.75% [9], 88.8% by Egilmez *et al*., [7] and 84.4% by Giannakakis *et al*., [3]. Simply using the Galvanic Skin Response signal, the authors in Ayata *et al*., [10] were able to attain arousal and valence accuracy rates of 81.81% and 89.29% respectively. When compared to non-overlapping window-based feature extraction, the application of convolution improved accuracy. In Lutin *et al*., [11], an SVM classifier was created using feature selection within a Leave-One-Subject-Out Cross Validation (LOOCV) setup. The resulting classifier has an accuracy of 88.52 %, a sensitivity of 72.50 %, and a specificity of 93.65 %.

A 72% accuracy in identifying stress levels was calculated [1]. According to a one-tailed Spearman's Rank Correlation coefficient test, this system is very capable of effectively and consistently assessing a person's level of mental stress, and researchers Setiawan *et al.*, [2] stated that under stable situations, the system can operate with an accuracy of 80%. The stress detection results from the RF and AB algorithms were acceptable, validating the paper's experimental study [6]. A study in Rodríguez-Arce *et al.*, [8] found that combining the KNN classifier with HR, ST, oximeter data, and four physiological features, students' stress could be identified with greater than 90% accuracy. SVM classifier with GSR signal and three physiological features could detect anxiety with over 95% accuracy. Lastly, the authors in Kontaxis *et al.*, [4] explained that SVM was able to distinguish between stress and relaxing stages with an accuracy from 68% until 89%. To conclude for all the studies done, SVM produced the best results among all the classifiers [5].

3. Materials and Methods

An alternate technique will be implemented which utilizes an online dataset that is a multimodal databaASe for impliCit pERsonaliTy and Affect recognitIoN, also known as the ASCERTAIN dataset [22]. This dataset will be used to complete the emotion recognition using the GSR signal project.

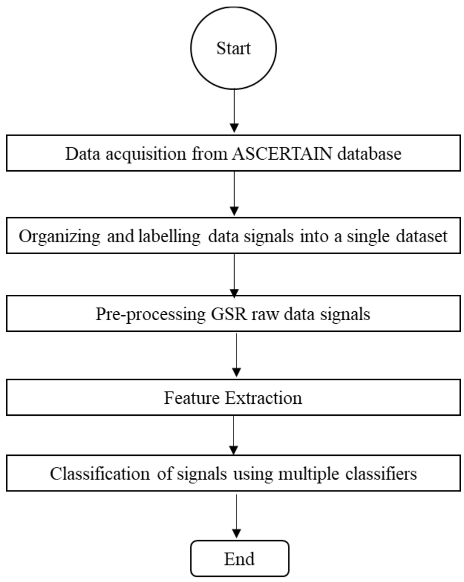

Fig. 1. Methodology of the project

The general processes in this project shown in Fig. 1 begin with acquiring GSR data signals from the available online dataset known as ASCERTAIN database. Next, organize and label the GSR raw data signals into a single dataset. After that, GSR raw data signals undergo the pre-processing and feature extraction steps by implementing the machine learning algorithm. Finally, import the features table and class label into the Classification Learner application in MATLAB software to train and test GSR data signals using various classifiers.

3.1 Data Pre-processing

Each dataset's information is filtered before being made accessible. In a separate file, the creators of the ASCERTAIN dataset provide information on the degree of noise and identified mistakes [22]. In addition, they state how confident they are in the information acquired from each user-generated video clip. To prevent a classification error, data streams with high noise or those labelled as having poor confidence by their producers are excluded from consideration.

Fig. 2 shows the extracted ASCERTAIN database process. The initial stage of data pre-processing involved 58 samples and 36 movie clips. The dataset consists of different physiological responses, but this project only used the GSR data signals. In contrast, each movie clip has selected the compilation arousal (A) rating representing the user's emotional perception

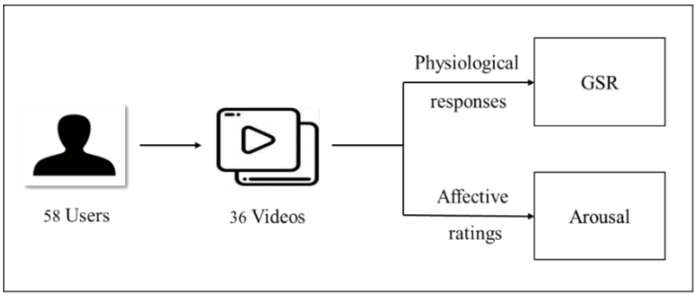

Fig. 2. Extract ASCERTAIN database

3.2 Feature Extraction

The original signals will be filtered with a high pass filter in an algorithm for machine learning. The objective of this filter is to generate a signal that is smoothed, hence lowering the noise of GSR data signals. Then, different features from the filtered and unfiltered signals will be extracted using the *signalTimeFeatureExtractor* and *signalFrequencyFeatureExtractor* objects. These objects allow performant computation of multiple features in the time and frequency domains with one function call. Besides this, the maximum number of peaks is set to 6, and the minimum distance between each spectral peak is set to 0.25Hz. Additionally, the FFT length of 256 and rectangular window of each 58 samples were selected to compute the spectral estimates.

Time domain waveform analysis is fundamental because it can control the number of samples and sample rate for a specific condition monitoring technique [19]. A Fast Fourier Transform (FFT) processing system builds into most portable vibration signal measuring devices. The FFT system aids in converting time-varying signals to appropriate frequency domains and breaking them into their constituent frequency components [24]. In addition, more sophisticated signal processing methods are now available, including wavelet transform, log-spectrum, Short Time Fourier Transform (STFT), and spectrum analysis.

3.3 Classifiers

There are various classifiers available in Classification Learner application of MATLAB software. However, this project will be used six types of classifiers for the GSR signals classification on emotion recognition including Naïve Bayes (Kernel Naïve Bayes), Kernel (SVM Kernel), Support Vector Machine (SVM) (Quadratic SVM), Neural Network (Narrow Neural Network), k-nearest neighbors (KNN) (Weighted KNN) and Ensemble (Bagged Trees). The choice of classifier can significantly affect the recognition accuracy. Some recent papers have analyzed the comparison of classifiers over an extensive collection of data sets. Firstly, the Naive Bayes classifier has a solid mathematical foundation and stable classification efficiency. The Naive Bayes classifier is relatively simple based on a simple assumption that attributes are conditionally independent of each other when the target value is given [25]. Next, SVM are widely used classifiers in emotion recognition. SVM algorithm analyzes data for the analysis of regression and classification. It maps data into a high-dimensional function space and datasets can be classified even if the data does not separate linearly [26]. Han and Cha [27] achieved a recognition rate of 70.9% with audio features and 85.0% with visual features for four emotions using the SVM classifier. Besides, Neural Network have emerged as an essential tool for classification. Recent research activities in neural classification have established that neural networks are a promising alternative to various conventional classification methods. The effectiveness of neural network classification is empirically tested and successfully applied to various real-world classification tasks in industry, business, and science [28].

Moreover, KNN is a machine learning algorithm that uses data and identifies new datasets according to similarities. It works to evaluate the k-nearest neighbors based on the minimal distance from the test samples to the training dataset [26]. KNN classifier works very well with small and large data sets, and the learning process costs zero. It is also very robust to noisy training data. While in the bagging algorithms for the Ensemble classifier, the model built on bootstrap replicates the original training dataset with replacement. Each training data replica is then used in a classification iteration using a machine learning algorithm. The outputs from all iterations are combined by taking the average principle to assign classes' labels [29]. These different models of classifiers are used to determine which machine learning algorithm could obtain the best performance in recognizing the emotions from GSR signals.

4. Discussion

This section discusses the findings and analysis including its method simulations in MATLAB and problems encountered throughout the process of developing the project. The results obtained after training and testing the GSR raw data signals are shown. As mentioned previously, the performance of multiple classifiers was evaluated for GSR signal to determine the best accuracy emotion recognition.

4.1 ASCERTAIN Database

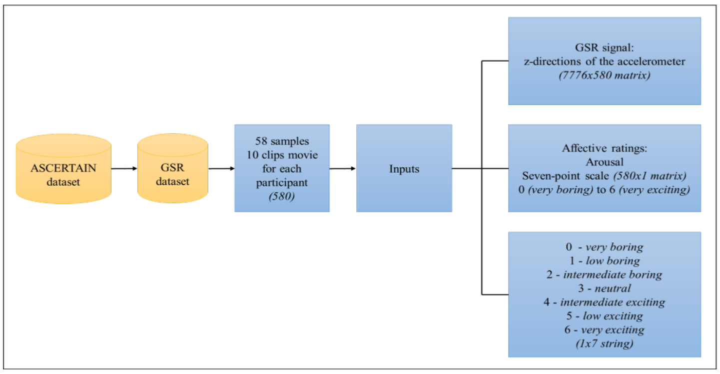

Fig. 4. Final extraction process of ASCERTAIN database

Fig. 4 describes the process of the final extracted ASCERTAIN database to acquire raw GSR data signals. Totally, the new dataset consists of each 58 samples (Movie_P01 – Movie_P58), and ten movie clips (GSR_Clip1 – GSR_Clip10) have been selected to sum up 580 samples (58 samples x 10 movie clips). There are a few inputs provided. Firstly, raw data GSR signals containing z-directions of the accelerometer are arranged in 580 by 7776 matrix to fit with the network. It represents 'atx' variable in MATLAB programming. Next, arousal (A) ratings reflecting the user's effective impression have been used with a seven-point scale starting from 0 *(very boring)* to 6 *(very exciting)*. A seven-point scale or class is arranged in a 1 by 580 matrix which is denotes to the variable 'actid.' In contrast, each scale represents the response vector, such as 0 is very boring, 1 is low boring, 2 is intermediate boring, 3 is neutral, 4 is intermediate exciting, 5 is low exciting, and 6 is very exciting. The variable indicates the response vector is 'actnames.' Finally, the dataset is saved in mat. file and named as 'FYP_ASCERTAIN_GSR. The following sections demonstrated the MATLAB machine learning algorithm, results for the confusion matrix, and the testing accuracy of each classifier.

4.2 Machine Learning Algorithm

Each subsequent section will provide an explanation of the machine learning algorithm that was constructed in MATLAB software along with specifics of the procedures that were engaged based on the emotion recognition pipeline.

4.2.1 Loading dataset

The process is started with the information of the new extracted dataset. FYP_ASCERTAIN_GSR.mat file consists of the information each type variables such as 'atx' represents the GSR raw data signals of fixed length (580 by 7776 matrix), 'actid' indicates the response vector containing the scale of emotion in integers (0, 1, 2, 3, 4, 5 and 6) which each integer representing different emotions such as Very Boring, Low Boring, Intermediate Boring, Neutral, Intermediate Exciting, Low Exciting and Very Exciting, respectively (580x1 double), 'actnames' represents the list of type of emotion names for each scale arranged in 1x7 string and 'fs' denotes to the sample rate accelerometer data.

4.2.2 Pre-processing signal

In this case, a high-pass filter applied to filter GSR raw data signals. The aim for this filter is to obtain a smoothed signal, reducing the noise of data streams. While the amount of GSR data down sampled to 128 Hz that provided by the detailed from ASCETAIN database and to avoid irreversible loss of information.

4.2.3 Feature extraction

The extraction of different features from filtered and unfiltered signals utilizes the *signalTimeFeatureExtractor* and *signalFrequencyFeatureExtractor* objects. These objects enable the efficient computation among many features in the time and frequency domains with a single function call. Configuring two *signalTimeFeatureExtractor* objects for time features. One is employed to extract the mean of the unfiltered signals (meanFE), while the other is employed to obtain the root mean square, shape factor, peak value, crest factor, clearance factor, and impulse factor of the filtered signals (timeFE). Another *signalFrequencyFeatureExtractor* is utilised to extract the mean frequency, band power, half-power bandwidth, peak amplitude, and peak location of the filtered signals' frequency features.

By adjusting other parameters, the computation of spectral peaks can be improved. For example, the maximum number of spectral peaks is set to 6, and the minimum spacing between each peak is set at 0.25Hz. In addition, a 256-length FFT and a 58-sample rectangular window are utilised to generate the spectral estimations. Besides, the computation of signal characteristics can be parallelized by using modified array datastores. Moreover, the datastores read each matrix column and compute the features by using the extract function of the feature extractor objects. Overall, the computed features are then merged to get 22 features for each of the 7776 signal observations.

4.2.4 Train classifiers using extracted features

For the training of the multiple classifiers, the features and activity labels are generally imported into the Classification Learner application that is available in MATLAB software. Alternatively, in this machine learning algorithm, the Support Vector Machine (SVM) classifier template is created using a feature table containing the features as the predictors and the activity labels as the responses.

The dataset should be partitioned in such a way that 75% of the signals are used for training and 25% are used for testing. The *cvpartition* function was used to ensure that each partition has activity labels in proportions that are comparable to one another. After train the classifier, test the classifier on the test partition. Lastly, the output of confusion matrix from the test classifier is produced to analyze the classification accuracy.

4.3 Classifiers

This section will further discuss on each of the confusion matrix produced by each classifier after the train and test process. The performance of GSR signal classification for emotion recognition using various classifiers was evaluated by giving the best accuracy in percentage form. The following section shows the result of confusion matrix for each test classifier.

4.3.1 Naïve Bayes classifier

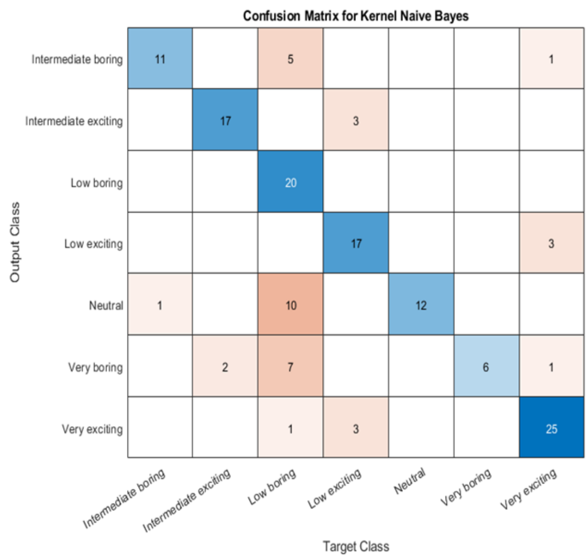

Fig. 9. Confusion matrix for Kernel Naïve Bayes

As can be seen in the Fig. 9, most of the errors occur when misclassifying the emotions of intermediate boring as neutral, intermediate exciting as low exciting and low boring as very exciting.

Overall, this classifier performed the GSR signal classification of emotion recognition with 74.5% accuracy.

4.3.2 Kernel classifier

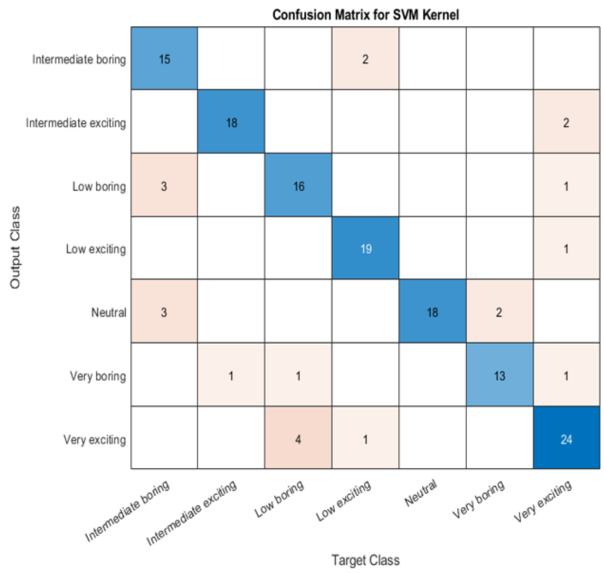

Fig. 10. Confusion matrix for SVM Kernel

Next, Fig. 10 is demonstrating the confusion matrix with errors occur when misclassifying the emotions of very boring as intermediate boring, low boring as intermediate exciting and neutral, low exciting as very exciting. Hence, SVM Kernel classifier performed the GSR signal classification of emotion recognition with 84.8% accuracy.

4.3.3 Quadratic SVM classifier

In Fig. 11 shows the confusion matrix for Quadratic SVM classifier where most of the errors occur when misclassifying the emotions of intermediate boring as low exciting and intermediate exciting as low boring as neutral. To sum up, Quadratic SVM classifier performed the GSR signal classification of emotion recognition with 91.7% accuracy.

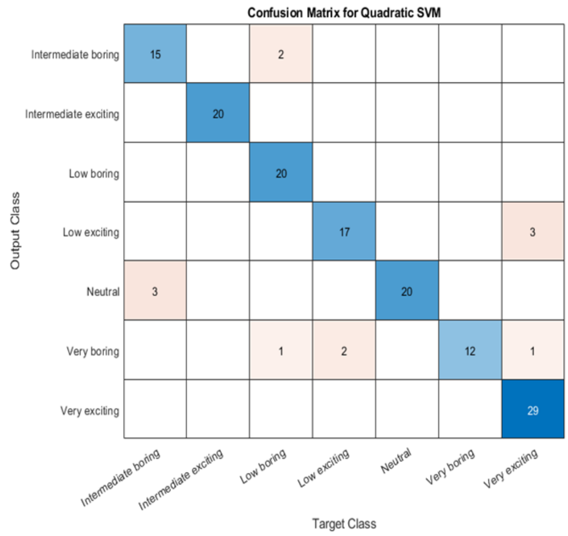

Fig. 11. Confusion matrix for Quadratic SVM

4.3.4 Neural network classifier

The test confusion matrix for Narrow Neural Network classifier is shown in Fig. 12. From the result, most of the errors occur when misclassifying the emotions of intermediate boring and low exciting as intermediate exciting and low boring and neutral as very exciting. Thus, this type of Narrow Neural Network classifier performed the GSR signal classification of emotion recognition with 96.6% accuracy.

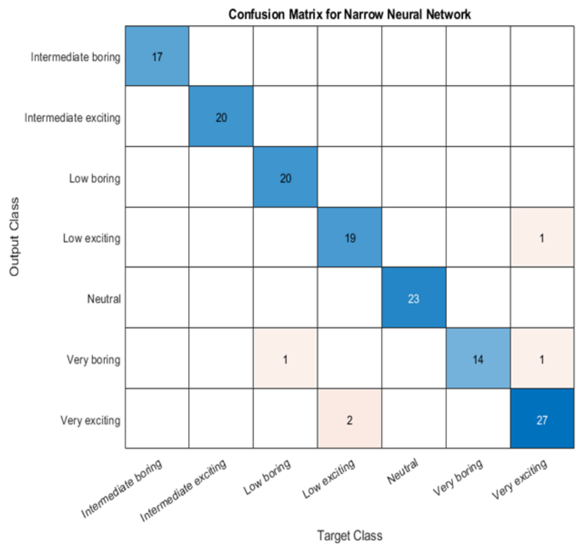

Fig. 12. Confusion matrix for Narrow Neural Network

4.3.5 KNN classifier

Furthermore, as can be seen in Fig. 13, most of the errors occur when misclassifying the emotions of intermediate boring and low exciting as intermediate exciting and low boring and neutral as very exciting. In short, the Weighted KNN classifier performed the GSR signal classification of emotion recognition with 97.9% accuracy.

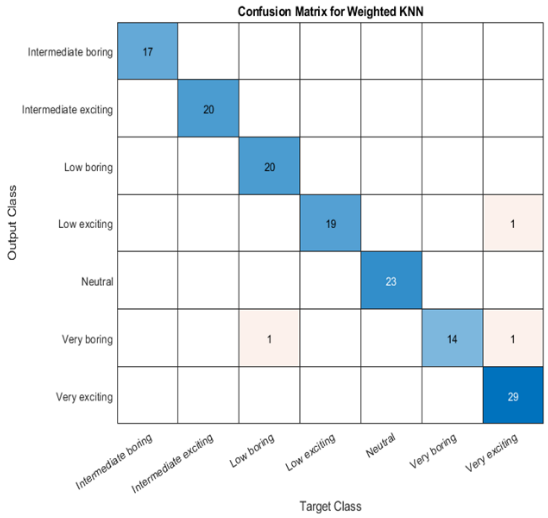

Fig. 13. Confusion matrix for Weighted KNN

4.3.5 Ensemble classifier

Lastly, the test confusion matrix for ensemble of bagged trees classifier as shown in Fig. 14. From the result the classifier demonstrated the same result as weighted KNN classifier, most of the errors occur when misclassifying the emotions of intermediate boring and low exciting as intermediate exciting and low boring and neutral as very exciting. Moreover, both of type weighted KNN and ensemble bagged trees classifiers also performed the GSR signal classification of emotion recognition with 97.9% accuracy.

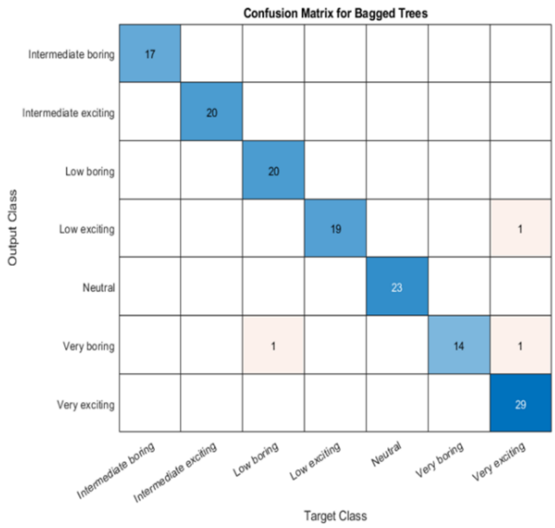

Fig. 14. Confusion matrix for bagged trees

Table 1 and Table 2 show the overall results obtained from the train and test of the GSR signal classification for emotion recognition performed by each of the six classifiers. As stated earlier, the features and activity labels are generally imported into the Classification Learner application that is available in MATLAB for training and testing these various classifiers. 75% of the GSR signals were used for training where the ensemble classifier demonstrated the highest accuracy which is 91.6%, followed by KNN (88.8%), Quadratic SVM (84.6%), neural network (81.1%), SVM Kernel (77.6%) and Kernel Naïve Bayes classifier (74.8%).

Table 1
Result of train multiple classifiers

Classifier	Type	Train Accuracy (%)
Naïve Bayes	Kernel Naïve Bayes	74.8
SVM	Kernel	77.6
SVM	Quadratic SVM	84.6
Neural Network	Narrow Neural Network	81.1
KNN	Weighted KNN	88.8
Ensemble	Bagged Trees	91.6

The primary focus is on the result of test classifiers, as shown in Fig. 9. The test of multiple classifiers contained 25% of GSR data signals, resulting in ensemble and KNN classifiers demonstrating the best accuracy with 97.9%, respectively. Then, followed by a neural network (96.6%), Quadratic SVM (91.7%), SVM Kernel (84.8%) and Kernel Naïve Bayes classifier (74.5%). The best outcomes are required to complete this project's objective, yet perfect precision did not attain. When working with input signals, which have a lot of noise from several users and multiple samples obtained from each of them, it is challenging to achieve a perfect result. Additionally, there is a significant range of variation across individuals while working with affective states. Since it is subjective, two users may transmit radically different affective states for the same video clip. Along these, the intensity of the same affective experience offered by the same user can change. Therefore, the results obtained can be considered enough for the final purpose.

An ensemble classifier's decision tree can easily be over-fitted, producing an excessive number of branches that may reflect abnormalities driven by noise or outliers [29]. While KNN Is a very straightforward technique for classifying data. First and foremost, KNN is known as a "lazy learner" because it does not learn new information during training. The training data are not used to derive any discriminative function. Furthermore, it maintains the training dataset and only uses the information it contains to make predictions in real-time. The KNN technique is much faster than other algorithms, such as the SVM classifier, which requires training. Also, the KNN algorithm does not require training before producing predictions. Therefore, new data is supplied without disrupting the system's performance. Other than that, it is indeed simple to implement KNN. The value of K and a distance function such as Mahalanobis are the only two parameters needed to implement KNN [30]. Hence, the significant advantage of KNN is that it is flexible in different proximity calculations based on the memory method and is very intuitive.

Table 2
Result of test multiple classifiers

Classifier	Type	Test Accuracy (%)
Naïve Bayes	Kernel Naïve Bayes	74.5
SVM	Kernel	84.8
SVM	Quadratic SVM	91.7
Neural Network	Narrow Neural Network	96.6
KNN	Weighted KNN	97.9
Ensemble	Bagged Trees	97.9

4.3 Comparison with Existing Approaches

Finally, after presenting the results obtained with the classification system, it is compared with results obtained using the similar ASCERTAIN database recently in 2020. The researchers in Muñoz-Saavedra *et al*., [18] presented their best result with valence (train) is 94.6%, arousal (train) is 95.9%, valence (test) is 90.4% and arousal (test) is 91.7% accuracies. This project's results are also detailed for training and testing subsets independently. However, it presents some deficiencies compared with this project.

The main difference from the existing work compared to this project, in Muñoz-Saavedra *et al*., [18] using many databases, including the ASCERTAIN and DREAMER databases, combined these two physiological signals such as ECG and GSR. In comparison, this project only uses the ASCERTAIN database and one physiological signal, GSR. Besides, Muñoz-Saavedra *et al*., [18] used three classification levels for each arousal and valence class: low, medium, and high. By comparing this project, the classification level increased into seven groups (0 – 6) for arousal representing very boring, low boring, intermediate boring, neutral, intermediate exciting, low exciting and very exciting, respectively.

Apart from that, the previous work [18] only performed a single classifier which is a neural network classifier compared, to this project performed six classifiers which are Naïve Bayes (Kernel Naïve Bayes), Kernel (SVM Kernel), Support Vector Machine (SVM) (Quadratic SVM), Neural Network (Narrow Neural Network), k-nearest neighbors (KNN) (Weighted KNN) and Ensemble (Bagged Trees). Overall, this project that uses an arousal seven-point scale obtains an accuracy greater than previous work, 97.6%, by both weighted KNN and ensemble bagged tree classifiers.

5. Conclusion

In conclusion, this work has shown a way of emotion recognition using GSR signal by developing the machine learning algorithm and Classification Learner application in MATLAB software. The GSR data signals from ASCERTAIN database are collected and extracted. The performance machine-learning algorithms were evaluated for GSR signal classification of emotion recognition using various classifier. The arousal seven-point scale (0 – 6) was utilized in the study to assign different emotions level for the class.

Six classifiers were trained and tested including Naïve Bayes (Kernel Naïve Bayes), Kernel (SVM Kernel), Support Vector Machine (SVM) (Quadratic SVM), Neural Network (Narrow Neural Network), k-nearest neighbors (KNN) (Weighted KNN) and Ensemble (Bagged Trees). The research objective is achieved with weighted KNN, and ensemble bagged trees classifiers and demonstrated the best 97.9% accuracy for emotion recognition. Based on the comparisons and results, it is proved that the methods used in this project are appropriate and easy to implement to detect the different emotions from GSR signals.

To improve the accuracy problem in the classification system, it is recommended to evaluate a few more techniques to improve this work in future work. Additionally, more features can be added such as movie clips in the dataset, resizing the matrix arrangement, performing a real-time emotion recognition using biofeedback GSR device such as Mindfield eSense Skin Response.

In brief, this work has successfully recognized emotions using a single GSR data signal. Further improvement in the development of technology detecting emotions will help the research in this field expand. These is due to the quality of the physiological signal acquired and more accurate emotion recognition techniques.

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