

EEG-based Negative Emotion Classification while Self Driving in a Simulated Environment

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ABSTRACT

The accuracy of the EEG signal analysis depends on the signal's quality, preprocessing, features and classification algorithm. This study explores the Self-Assessment Manikin (SAM) and electroencephalography (EEG) with machine learning to classify vehicle driver emotions. Using SAM, emotional states such as relaxation, focus, fear, nervousness and surprise were quantified on a scale of 1 to 5 during experimental scenarios. EEG signals, captured via the Emotiv Epoc X, underwent preprocessing with a 6th-order bandpass filter and zero-phase distortion filtering to minimize artefacts and preserve signal integrity. Five time domain features and three frequency domain features are extracted for the classification. The mutual information (MI) used to reduce the features number and selected the features with the most significance only. A k-Nearest Neighbors (KNN) algorithm and Random Forest (RF) were applied to classify emotion and evaluating accuracy. The classification accuracy for KNN and RF are 98% and 93% respectively. These findings could lead to improvements in affective computing and driver monitoring systems. Compared to the past EEG emotion studies that rely on large feature sets, this research introduces a compact feature selection method based on mutual information to identify the most discriminative EEG features for negative emotions in autonomous driving simulation.

Keywords: EEG, k-Nearest Neighbor (KNN), Random Forest (RF), Emotions Classification

1. INTRODUCTION

Recent advancements in neuroscience, psychology and artificial intelligence have led to an increase of interest in the study of human emotions and their underlying neural connections. This emerging research field aims to understand the relationships between emotional experiences and the brain's complex neural systems [1]. SAM helps researchers to measure the intensity of emotions such as relaxation, focus, fear, nervousness and surprise in a standardized and intuitive approach. This study used SAM to determine participants' emotion and level of engagement during experiments, scoring emotional intensity on a scale from 1 to 5. Another method to measure human emotions is by studying the human Electroencephalography (EEG) signals.

EEG has proven to be a reliable method for capturing neural activity associated with emotional states. But EEG signals are usually noisy and susceptible to artefacts such as changes in skin conductivity and muscle movements [2]. To remove artefacts and prepare data for analysis, effective preprocessing is important. This includes bandpass filtering [3][4][5] and normalization

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[6]. This study uses zero-phase distortion filtering to maintain signal integrity and a 6th-order bandpass filter to minimize the noises [7].

In the EEG signal analysis, feature extraction is an important step to translate unstructured data into usable representations. This research extracted the delta, theta, alpha, beta and gamma frequency bands from the EEG signal, which helps to capture the temporal and spectral dynamics, which is important for emotion classification.

Machine learning algorithms, such as the k-Nearest Neighbors (KNN), have proven their efficacy in classifying emotional states from EEG features [8][9][10]. KNN is preferred because of its simplicity and adaptability in handling nonlinear relationships in multidimensional datasets [11]. The quality of the features extracted, and the preprocessing methods used have a major impact on the classification performance. This study evaluates the effectiveness of KNN in classifying emotions based on features extracted from the pre-processed EEG data.

On the other hand, Random Forest (RF) is an ensemble learning algorithm widely applied in physiological signal processing because of its ability to handle noisy and multidimensional data. A key strength of RF is its ability to model complex, nonlinear relationships between features and labels. Unlike single decision trees that are sensitive to noise, RF combines many weak learners, producing a more stable and accurate model.

In this research, the combination of SAM-based emotional assessments with EEG signal processing and classifier (KNN and RF) provides a comprehensive framework for emotion classification. To determine which features are most useful for emotion recognition and to suggest methodological enhancements for further research, the classification is performed across different hyper parameter values. The performance of the classifiers is studied by quantifying the accuracies for all classification classes. An increased understanding of how emotion affects driving performance through the analysis of EEG signals provides a safer driving environment.

2. METHODOLOGY

The study employed a two-stage experimental design separating subjective emotion validation from physiological signal analysis. In the first stage, SAM questionnaires were collected from 16 participants who observed autonomous driving scenario videos and reported the emotions they perceived. This stage was intended to validate that the designed scenarios were capable of consistently eliciting target emotional responses across a broader participant population.

The second stage focused on EEG-based emotion classification, which required a fully immersive autonomous driving simulation involving interaction with a steering wheel, accelerator and brake pedals. Due to the increased experimental complexity, equipment preparation and signal quality requirements associated with EEG acquisition, about 18 participants completed this phase. Consequently, EEG analysis was performed using high-quality recordings obtained from these participants. This two-stage approach enables large-scale subjective validation while maintaining controlled physiological measurement conditions. In total, there are 34 results for the SAM questionnaire (18 are from the second stage), where the EEG signal was also recorded during the experiments, and the remaining are from the first-stage experiment.

Traditionally, SAM is used to study the impression or emotions that occur during the test or experiments. The analysis of the emotions can produce false results as sometimes the participants are not honest or not sure about their feelings [1]. The SAM questionnaire is also volatile as the surrounding situation and past problems can affect the participants' answers. By using the SAM results as a reference, the physiological analysis using electroencephalogram (EEG) provides a better understanding of human emotions while driving the vehicle [12][13][14].

The protocol for the EEG signal data collection is shown in Figure 1. The instructions were given after the participants arrived. Participants were selected across a broad demographic range, including variations in age and driving experience, to ensure the generalizability of the results. 18 participants are selected from university students with ages ranging from 19 to 35 years old. The driving experience of participants varied from 1 year to more than 10 years.

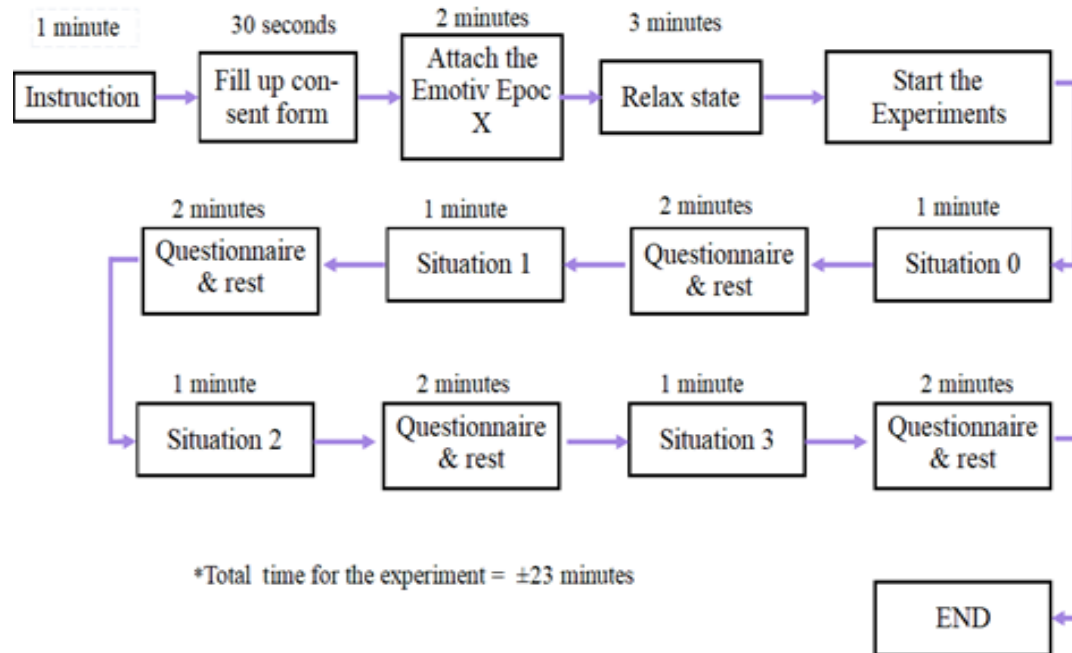


Figure 1. Process flow of the experiments for EEG signal acquisition

Then, the Emotiv Epoc X is attached to the participants. The Emotiv Epoc X is an EEG signal acquisition device with 128 signals per second (s.p.s.) sampling rate, resolution of $0.51\mu\text{V}$ and bandwidth from 0.16 to 43Hz. The electrode placement for the Emotiv Epoc X follows the 10-20 system for all 14 channels as shown in Figure 2.

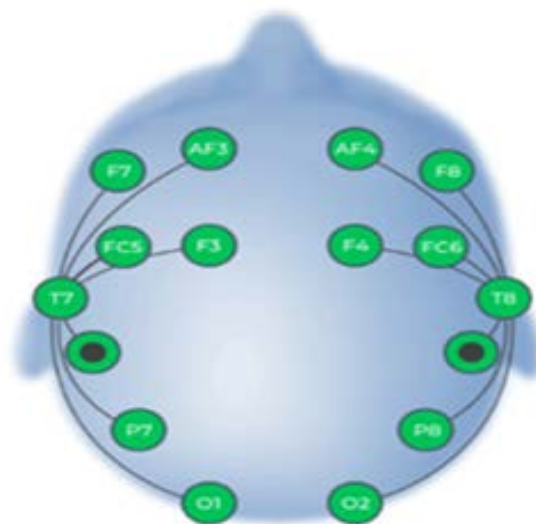


Figure 2. Electrode placement for Emotiv Epoc X using 10-20 system [15]

Three minutes of EEG signal baseline (relax state) were recorded before the experiment. During the baseline recording and rest, participants are subjected to relaxing audio and video to make

sure they are in a relaxed state. The experiments start with situation 0. For situations 1 to 3, the sequence of experiments is assigned randomly using the Latin square method. The Latin square method minimizes order effects to make sure there are unbiased emotional responses across scenarios. After each situation experiment (situation 0 to situation 3), participants were instructed to answer the SAM questionnaire. Experiments ended after participants experienced all the situations. The type of situations that the participants need to experience are not disclosed before the experiments.

Participants need to experience the autonomous driving environment in the virtual environments. Situations from 0 to 3 are the virtual environment developed to study the emotions of the vehicle driver. The description of the situation 0 to 3 are as follows:

- Situation 0 – Training phase where the participants familiarise themselves with the virtual environment, as shown in Figure 3.



Figure 3. Training phase

- Situation 1 – A situation where the lead car suddenly brakes in front of the participant's car, as shown in Figure 4.



Figure 4. Situation 1

- Situation 2 – A situation where a nearby car suddenly changes lanes into the participant car and can cause an accident, as shown in Figure 5.



Figure 5. Situation 2

- Situation 3 – A situation where the pedestrian crosses the road and causes a near accident with the participant car, as shown in Figure 6.



Figure 6. Situation 3

2.1 Self-Assessment Manikin (SAM) Questionnaire

The Self-Assessment Manikin (SAM) is used to determine the existence of specific emotions during the experiments. SAM is a graphical, nonverbal questionnaire that measures the person's affect or feeling response from external stimuli, videos or events [1]. The emotions (relax, focus, fear, nervous, surprise) were studied in this research. The severity of the emotions felt by the participants is quantified into 1 (none), 2 (low), 3 (medium), 4 (high) and 5 (very high) to determine the engagement. Figure 7 shows a part of the SAM used in the experiments. Overall, SAM assessments of the 34 participants have been collected.

INVESTIGATION OF HUMAN EMOTIONS WHILE DRIVING AN AUTONOMOUS VEHICLE IN SIMULATED VIRTUAL ENVIRONMENT BY USING EEG SIGNAL

SELF ASSESSMENT FORM

Subject ID: _____ Age: _____ Gender: _____
Driving experience (years): _____

1. Situation #0 (No situation)

1.1. Type of emotions for situation #0

a - Relax b - Focus (concentration) c - Nervous d - Surprise e - Fear

1.2. What is the intensity of emotion in situation #0

1 2 3 4 5

None Low Medium High Very High

2. Situation #1 - Sudden brake by the lead car

2.1. Type of emotions for situation #1

a - Relax b - Focus (concentration) c - Nervous d - Surprise e - Fear

2.2. What is the intensity of emotion in situation #1

1 2 3 4 5

None Low Medium High Very High

Figure 7. Self-Assessment Manikin (SAM) to determine the emotions that occur during the experiments

2.2 EEG Signal Analysis for Emotion's Classification

2.2.1 Preprocessing

The analysis of the EEG signals is nonstationary and susceptible to signal noise. The EEG signals exhibit nonstationary characteristics. The signal noises and artefacts in the EEG signals are caused either by the participants themselves or by recording devices (unstable impedance).

Muscle movements due to eye blinks, jaw clenching or facial expressions are examples of common artefacts [16]. Another common artefact includes changes in skin conductivity brought on by perspiration or shifts in the contact impedance between the electrodes and the skin [17]. Significant distortions may be introduced by these artefacts, especially in the lower frequency ranges where physiological signals predominate.

A 6th-order bandpass filter is used to reduce these effects by removing noises and artefacts while isolating the necessary frequency bands related to brain activity (e.g., delta, theta, alpha, beta and gamma). In order to work, the bandpass filter minimizes signals outside of a certain frequency range while allowing signals inside it to pass through (0.5 Hz to 49 Hz) [7]. Because of its severe roll-off, the 6th-order filter effectively separates the desired EEG frequencies from noise.

The final stage in the preprocessing is normalizing the signals. The frequency band values are normalized in the range of [0, 1]. EEG signals are sensitive to noise and artefacts [18]. Normalizing can minimize the effects of high-amplitude noise, making the features more reliable for classification [26]. The normalized equation is shown in Equation (1):

$$\text{Normalize signal} = \frac{\text{filtered signal} - \min(\text{filtered signal})}{(\text{filtered signal}) - (\text{filtered signal})} \quad (1)$$

The preprocessing step is to ensure that the filtered signals are both artefact-free and statistically accurate [4] by combining the 'filtfilt' function, high-order bandpass filter and normalize. This creates a strong foundation for feature extraction and classification tasks that followed.

2.2.2 Features Extraction

After the preprocessing process, the features are extracted. The extracted features consist of time domain and frequency domain features. For the time domain feature, the mean, standard deviation (std), skewness, kurtosis and entropy were extracted, and they show changes in amplitude, time scale and complexity. The features and their formulas are as shown in Equations (2) to (6):

$$\text{Mean, } \mu = \frac{1}{N} \sum_{i=1}^N x_i \quad (2)$$

$$\text{Standard deviation, } \sigma = \sqrt{\frac{1}{N} \sum (x_i - \mu)^2} \quad (3)$$

$$\text{Skew} = \frac{\frac{1}{N} \sum \{(x_i - \mu)\}^3}{\sigma^3} \quad (4)$$

$$\text{Kurtosis} = \frac{\frac{1}{N} \sum \{(x_i - \mu)\}^4}{\sigma^4} \quad (5)$$

$$\text{Entropy} = - \sum p(x_i) \log_2 p(x_i) \quad (6)$$

Power, relative power and peak power for the 5-frequency band (delta, theta, alpha, beta and gamma) were extracted for the frequency domain features and their power intensity within specific frequency bands. The frequency domain features used and their formulas are as listed in Equations (7) to (9):

$$\text{Absolute power band, } P_{\text{band}} = \int_{f_{\text{low}}}^{f_{\text{high}}} \text{PSD}(f) df \quad (7)$$

$$\text{Relative band power, } RP_{\text{band}} = \frac{P_{\text{band}}}{P_{\text{total}}} \quad (8)$$

$$\text{Peak frequency, } f_{\text{peak}} = \text{argmax} (\text{PSD}(f)) \quad (9)$$

The features were then reduced by using the Mutual Information (MI) method. The number of features reduces from 8 (time and frequency domain) to 2 features as only two features (entropy and standard deviation) gave highest MI score, which contributes to a better classification accuracy.

2.2.3 Classification

The classification of drivers' emotions was designed to examine their reactions to near-miss accident situations. The classification method used were KNN and RF. The classifier used to class the EEG emotions data into 5 different classes, which are surprise, relax, nervous, focus and fear as shown in Table 1, together with their respective valence and arousal. The hyper parameter modified to improve the classification accuracy. The performance of both classifiers was compared. The performance for the interest emotions classification of all 18 participants was studied. The performance of the classifier is measured using accuracy, precision, recall and F1-score.

Table 1 Emotions studied in this research

Emotions	Valence arousal chart
Focus, surprise	High valence, high arousal
Nervous, fear	Low valence, high arousal
Relax	High valence, low arousal

KNN is a simple, non-parametric, and effective supervised learning algorithm used for classification and regression tasks. KNN classifies the new data by calculating the distance of the new data to the data point created during the training phase. The new data is classified into specific classes that have similarities with the data point.

The hyperparameter k is used to determine the number of the nearest neighbour to predict the test data classes. The distance of the test data to the nearest neighbour is commonly calculated either using the Euclidean distance, Manhattan distance or Minkowski distance. The Euclidean distance was selected for this research to calculate the distance. The Euclidean distance between two points is calculated using Equation (10):

$$d(x, y) = \sqrt{\sum (y_i - x_i)^2} \quad (10)$$

where d (x, y) is the distance between two points. The interest point's x- and y-coordinates are used to calculate the distance between two points.

The distribution of the training and test data is divided as follows: 70% for training and 30% for testing. The datapoint for the training and testing are 451. The k-fold validation method is used

to divide the training and test data. In order to reduce the computation time and extensive use of the computing power, this paper only covers the 5-fold validation. K-fold validation reduces the possibilities of overfitting or underfitting because all data is used for both training and testing if compared to a single train-test split performance model [19][20].

The classification accuracy will be investigated by classifying the emotions using one frequency band, two pairs of frequency bands and lastly the combination of three frequency bands.

Meanwhile, the RF model is the advanced model of the decision tree as the RF uses multiple trees. The parameter values such as leaf number, split number, number of trees can affect the classification accuracy. After several parameter tuning, it is found that the suitable hyperparameter is as listed in Table 2.

Table 2 Hyperparameter tuning for the RF classifier

Hyperparameters	Values
Number of decision trees (n_estimator)	100
Number of levels (Max depth)	None
Minimum number of samples a node must have before it can be split (Min samples split)	2
Minimum number of samples in a leaf node (Min sample leaf)	1

The number of levels for the RF is set to “None” which indicating that the individual decision trees were allowed to grow until all leaves were pure or until the minimum sample requirements for splitting were met. This unrestricted depth allowed the model to capture detailed patterns in the EEG data while maintaining robustness through ensemble averaging. The 5-fold cross validation was used to reduce the overfitting and underfitting. The training to test data ratio is 70%: 30%. The datapoint for the training and testing are 451.

2.3 Performance Analysis

The statistical analysis method was used to determine the performance of the classifiers. The precision, recall and F1-score were calculated to determine the performance. The precision calculates the positive prediction to minimise the false positive (FP). The precision shows the true positive (TP) prediction produced by the classifier, while recall or sensitivity calculates how many models identify positive classification. It used to minimise the false negative (FN). F1-score combines the recall and precision measurements. It shows the classifier effectiveness (precision & recall) in a single number. The mathematical equations for precision, recall and F1-score are shown in Equations (11) to (13). Figure 8 describes the confusion matrix for the performance metric analysis.

$$\text{Precision} = \frac{TP}{TP+FP} \quad (11)$$

$$\text{Recall} = \frac{TP}{TP+FN} \quad (12)$$

$$\text{F1 - score} = \frac{2TP}{2TP+FP+FN} \quad (13)$$

		TEST RESULTS	
		Positive	Negative
CONDITION	Positive (P)	True Positive (TP)	False Negative (FN)
	Negative (N)	False Positive (FP)	True Negative (TN)

Figure 8. Confusion matrix for the performance analysis [21]

3. RESULTS AND DISCUSSION

3.1 Self-Assessment Manikin (SAM)

The SAM questionnaire collects the participants' thoughts after each experiment. The questionnaire of the emotions felt by 34 participants during the experiments and their intensity is represented in a box and whisker as shown in Figure 9. Table 3 shows the hypothesis drawn from past research and compares it with the current SAM questionnaire response. The triggered emotions are varied as the driving experience, age, gender, social and education background can affect the emotions responses [22][23].

Theoretically, participants may experience surprise when they encounter an abrupt situation [24], such as a pedestrian crossing the road suddenly; fear when they experience a reflex reaction to avoid danger [25], such as when the front car brakes suddenly; nervousness when they feel threatened by the situation, such as when a nearby vehicle makes a dangerous overtake manoeuvre; and relax emotions are used as a baseline for the emotions classification [26].

The age and the driving experience of the participants are varied. The average participant's age is 25.85 years old with a standard deviation of 7.16 years. The driving experience of the participants ranges from 1 year to more than 10 years of experience. The difference in driving experience and ages gave diverse responses from the participants, as a lot of other variables can change the participants emotions [26].

The response from SAM questionnaire varied as shown in Figure 9 as well as in Tables 3 and 4. The semantic differential responses across different emotions states shown in Figure 9. Situation 0 shows the mixed reaction from the participants. The participants either felt 'relax' or 'focus'. The situation also occurs for other emotions such as surprise, nervous and fear. This is due to the driving experience and exposure towards the autonomous vehicle. The summary of the triggered emotions for all situations simulation is summarized as in Tables 3 and 4.

Table 3 shows the difference between hypothesis and triggered emotions. The emotions triggered are varied from one participant to another. Even though the designed situation was a hypothesis to trigger specific emotions, in the real experiments, the participants' reactions varied based on their experiences. Table 4 shows the distribution of emotions triggered during the experiments. The table shown the percentage of the triggered emotions on each situation for all the participants from the SAM questionnaire. The conclusion for the dominant emotions triggered

cannot be made as the target for the SAM questionnaire respondent is 50. Currently, the results show 34 participants only.



Figure 9. SAM questionnaire distribution

Table 3 Induced emotions between hypothesis and experiments

Situation	Hypothesis	Triggered emotions
0	Focus	Relax / focus / nervous
1	Fear	Surprise/ nervous / fear
2	Nervous	Surprise/ focus / fear / nervous
3	Surprise	Surprise / Fear

Table 4 The percentage distribution of the emotions triggered by the participants

Emotions	Situation 0	Situation 1	Situation 2	Situation 3
Relax	32.35%	2.94%	0.00%	0.00%
Focus	29.41%	5.88%	23.53%	5.88%
Nervous	26.47%	20.59%	17.65%	17.65%
Surprise	5.88%	50.00%	41.18%	44.12%
Fear	5.88%	20.59%	17.65%	32.35%
Total contribution of emotion	100%	100%	100%	100%

3.2 Emotions Classification

3.2.1 Pre-processing

Figure 10 (a), (b) and (c) shows the differences between the raw signals, signals after the bandpass filter and normalized signals. The 6th-order Butterworth filter is proven to remove the noises and artefacts from the raw data as shown in Figure 10 (b). EEG signals from different channels or frequency bands often vary in amplitude. Normalization scales all signals to a uniform

range [0, 1], thus making sure that all features contribute equally to the classification model performance as shown in Figure 10 (c).

Several features extracted from the normalized signal such as mean, standard deviation, skewness, kurtosis, entropy, absolute power band, relative power band and peak frequency. The mutual information (MI) method used to reduce the less significant features. Features with the highest contribution used for the emotion's classification. Figure 11 shows the features with the highest MI score. Based on the MI analysis, only entropy and standard deviation feature significantly help in the emotion's classification (MI score > 0.3).

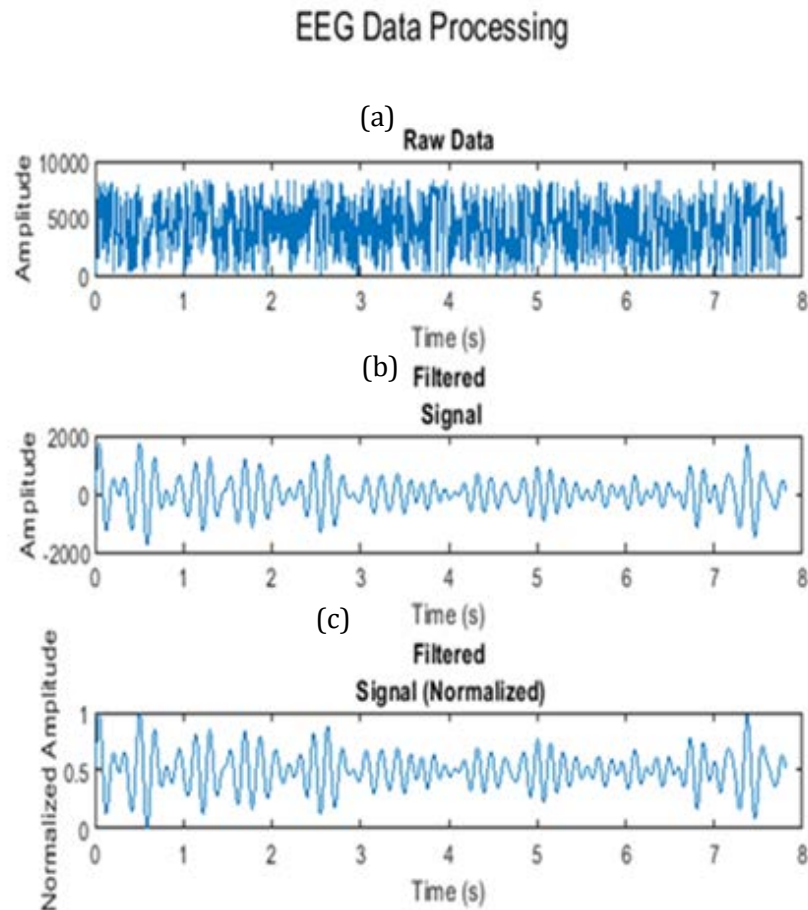


Figure 10. EEG signal pre-processing

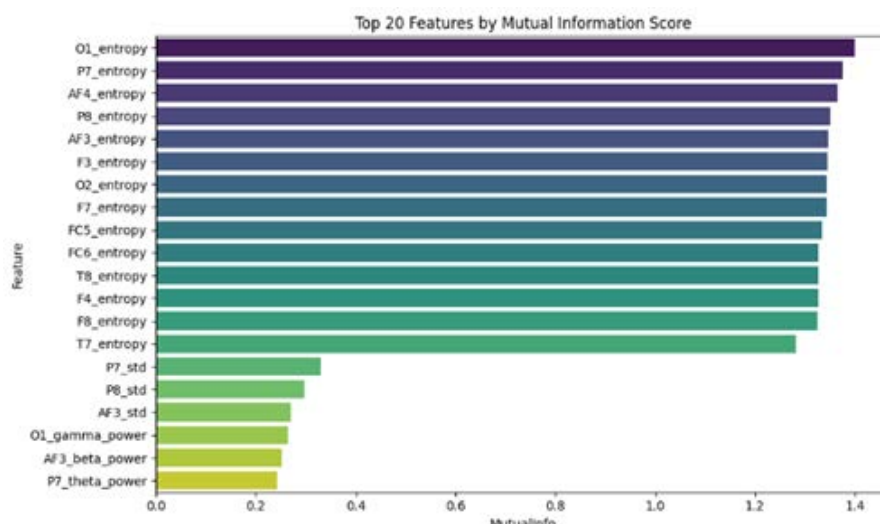


Figure 11. EEG signal pre-processing

3.2.2 KNN Classification Performance

KNN achieved an overall accuracy of 98%, with perfect classification for relax, focus, and nervous states, and strong performance for fear and surprise (F1-scores of 0.95) as shown in Table 5. The high performance demonstrates that negative emotions can be reliably identified from EEG features, particularly entropy and standard deviation. KNN’s effectiveness here reflects its strength in handling small, well-separated feature spaces, where decision boundaries are relatively simple.

After parameter tuning, it is found that $k=1$ produced highest classification accuracy for ‘surprise’ emotions and can separate the classes better as shown in Figure 12. There are small misclassifications as the surprise emotion predicted as fear emotion. During the fear prediction, some of the test data shown that the model misclassified it as surprise. Due to their high-arousal status, both emotions might result in overlapping EEG patterns, which can cause boundary ambiguity in a distance-based classifier. The overall performance, however, shows that KNN worked well when the dataset distribution was compact and well-structured and successfully captured local feature similarities.

Table 5 Performance metric for the KNN classification

Emotions	Precision	Recall	F1-score
Fear	0.90	1.00	0.95
Focus	1.00	1.00	1.00
Nervous	1.00	1.00	1.00
Relax	1.00	1.00	1.00
Surprise	1.00	0.91	0.95

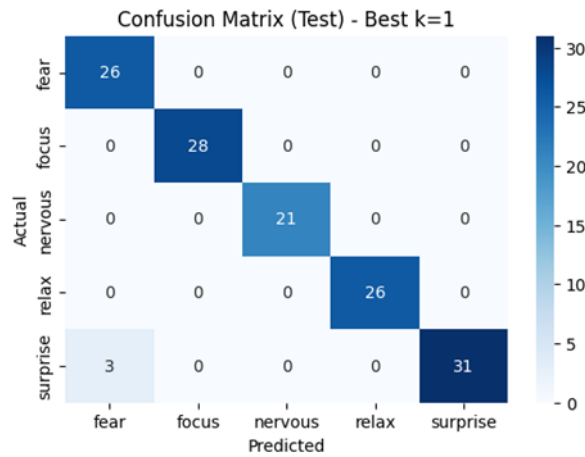


Figure 12. Confusion matrix for KNN classifier

3.2.3 RF Classification Performance

RF achieved 93% accuracy, slightly lower than KNN as shown in Figure 13. While RF is typically robust in noisy or high-dimensional datasets, its performance here may have been limited by the small dataset (18 participants) and the reduced feature space.

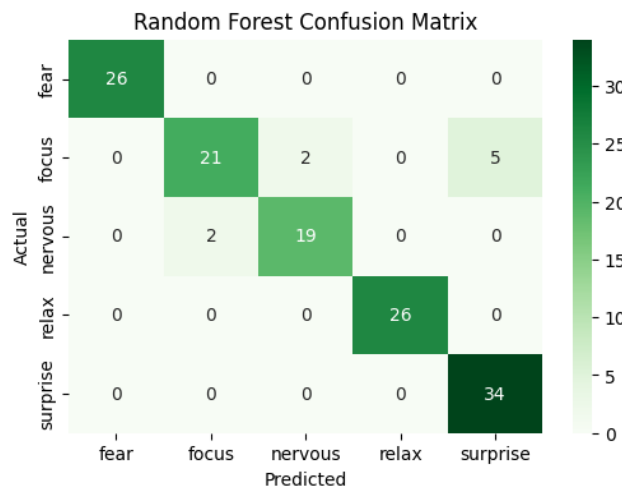
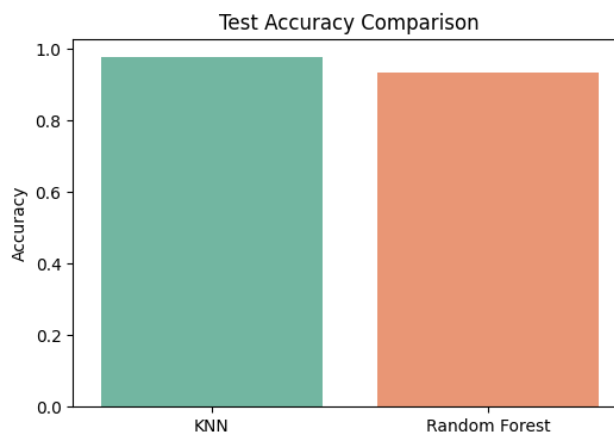


Figure 13. Confusion matrix for RF classifier

Nevertheless, RF performed strongly for fear (F1-score = 1.0) and nervousness (F1-score = 0.90) as in Table 6, showing potential for real-world implementation where more diverse features and larger datasets may favour ensemble learning. Figure 13 also shows surprise' emotion is highly classified compared to other emotions, while a small portion of data (focus and nervous) misclassified as nervous, focus, and surprise. Misclassifications primarily happened between focus, nervous and surprise states, suggesting that when only a small number of features were employed, ensemble-based decision boundaries were less successful in distinguishing classes with modest differences. RF often performs better in high-dimensional environments with more feature diversity, the model's capacity to take advantage of its ensemble advantages may have been constrained by the smaller feature set acquired through MI. Figure 14 compares the overall classification results, proving that KNN performs better than RF.

Table 6 Performance metric for the RF classification

Emotions	Precision	Recall	F1-score
Fear	1.00	1.00	1.00
Focus	0.91	0.75	0.82
Nervous	0.90	0.90	0.90
Relax	1.00	1.00	1.00
Surprise	0.87	1.00	0.93

**Figure 14.** Comparison of the classification accuracy (KNN and RF)

4. CONCLUSION

The integration of the Self-Assessment Manikin (SAM) questionnaire with EEG-based machine learning classification provides a comprehensive framework for emotion recognition in simulated autonomous driving environments. The SAM results confirm that hazardous driving scenarios successfully induce negative emotional states, although the responses vary across participants due to differences in personal perception, experience and demographic factors. This variability highlights the inherent subjectivity of questionnaire-based emotional assessment.

In contrast, EEG-based classification offers an objective evaluation of emotional responses by analysing brain activity patterns. The high classification performance achieved by KNN (98%) and Random Forest (93%) demonstrates that the selected EEG features, namely entropy and standard deviation, contain discriminative information capable of separating emotional states reliably. The consistency between SAM-reported emotions and classifier outputs indicates that the physiological responses captured through EEG align with participants perceived emotional experiences.

RF, while generally robust for high-dimensional or noisy data, may not have benefited from the limited diversity of features in this dataset. Importantly, KNN's relatively low computational complexity makes it well-suited for real-time driver monitoring applications. Ensemble methods such as RF generally benefit from richer feature diversity, whereas KNN capitalized on the clear separability of the two or more selected features. The SAM results confirmed that hazardous driving events reliably trigger negative emotions, though with variability influenced by age, experience, and individual perception. This suggests that emotion-aware systems should be adaptive rather than a general model that fits all users.

Despite the promising results, several limitations should be acknowledged. The sample size was smaller than the intended target, which may restrict the generalizability of the findings. Additionally, all participants were university students, limiting demographic diversity, and the study was conducted entirely in a simulated driving environment. These controlled conditions may not capture the full complexity of real-world driving, where factors such as traffic density, environmental stressors, and fatigue can influence emotional states.

Overall, the findings suggest that SAM and EEG-based classification should not be viewed as competing methods but rather as complementary approaches. While SAM provides psychological grounding and experimental validation, EEG classification enables continuous, real-time, and unbiased emotion detection. This combined methodology strengthens the reliability of emotion recognition systems and supports the development of adaptive driver monitoring frameworks for autonomous vehicles.

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