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Analysis and Processing of Driver Behavior for Emotion Recognition

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Abstract Road traffic injuries cause considerable economic losses to individuals, families and nations. Knowing the driver's condition means continuously recognizing whether the driver is physically, emotionally and physiologically fit to drive the vehicle, as well as effectively communicating these situations to the driver. This research aims to collect, analyze and process behavioral signals in drivers through the interaction of the driver with the basic elements of driving to recognize different types of emotions established in the continuous model of emotional characterization proposed by Russell using emotion induction through augmented autobiographical recall and machine learning algorithms, in order to generate models capable of recognizing the emotional state of drivers through a minimally invasive, objective and efficient process. With this methodology of signal analysis of driver behavior, 4 types of emotions could be recognized within the two-dimensional excitation-valence plane with an accuracy of 73 % using the Random Forest algorithm. In conclusion, a first scientific perspective on the relationship between driver behavior and emotions is offered, and the most significant information signal windows for emotion identification in a simulated driving experimentation environment are successfully identified.

Keywords: Emotion recognition, Machine learning, Driver behavior, Emotion induction, Artificial intelligence

1. Introduction

Each year, the lives of approximately 1.3 million people are cut short because of a traffic accident. An additional 20 to 50 million people suffer non-fatal injuries, and many suffer a disability by injury. Road traffic injuries cause considerable economic losses to individuals, families and nations as a whole [53]. This is because vehicle drivers must process a continuous flow of information that comes in the form of visual information. This includes the road, road signs, pedestrians, other cars, the environment, etc. In addition, the drivers will have a lot of thoughts, such as trying to remember the day's tasks, remembering directions, worrying about something, and so forth [1].

There is the possibility that the driver is exposed to other stimuli that may reduce the processing capacity of the human brain, for example, a driver under the influence of alcohol and/or any substance or drug increases the risk of a motor vehicle crash, which may result in death or serious injury to vehicle occupants [6]. Similarly, the literature review suggests considering other factors to predict the risk of

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driving behaviors such as personality, attitude and risk perception [38], personality, and attitudes from which emotions transcend [37].

The safe road systems approach aims to ensure a safe transportation system for all vehicle users. This approach considers the vulnerability of people to serious injury in road crashes and recognizes that the system must be designed to accommodate human error [54]. Knowing the driver's condition means continuously recognizing whether the driver is physically, emotionally and physiologically fit to steer the vehicle, as well as to effectively communicate these situations to the driver. Affective computing, whose main objectives are to create machines capable of adapting to users' emotions to achieve a natural and efficient interaction [22], combined with advanced driver assistance systems (ADAS). Besides, Emotion recognition can enable machines to understand human emotions and has extremely important application prospect. In human-computer interaction (HCI), emotion enables the robot to make corresponding feedback according to the user's emotional state to improve the quality of human-computer interaction [7]. In other words, the machines are unable to identify human emotional states and use this information in deciding upon proper actions to execute [32].

However, most current ADAS systems implement only simple mechanisms to consider drivers' emotional states, if these systems were informed about the driver's emotional state, could make contextualized decisions compatible. Knowing the driver's state means continuously recognizing whether the driver is physically, emotionally and physiologically fit to steer the vehicle, as well as effectively communicating these situations to the driver. Implementing an ADAS system in a vehicle, to monitor the alertness and performance of drivers, is not trivial to develop and in fact, presents many problems [8].

Emotion recognition is therefore a central component of the field and is based on a variety of measurements (facial expressions, speech, gait patterns, physiology, eye tracking, etc.) that are analyzed using advanced pattern recognition techniques [59, 25].

To understand these emotional states, are often classified within basic emotion categories [31] or on continuous scales with arousal and valence dimensions (Russell, 1980). In the context of driving, medium arousal is considered the optimal level of arousal [9], and positive valence is often desired as a sign of a good user experience. In this implements the continuous emotion characterization model that consists of using several mutually orthogonal basic axes to show different dimensions of emotion, which resolves the contradiction between the discrete quantification method and emotional connotation [19]. The valence-arousal is the most applied due to its low simplicity of integration into an emotion assessment questionnaire and low complexity in the modeling of Machine Learning (ML) algorithms, attaining overall good results [3].

Recent developments in deep learning have substantially advanced image recognition tasks, particularly in applications related to Advanced Driver Assistance Systems (ADAS). Convolutional Neural Networks (CNNs) remain a reliable architecture for extracting spatial features, but recent contributions have demonstrated that Vision Transformers (ViTs) can outperform CNNs in modeling long-range dependencies and global context in remote sensing imagery [45]. Hybrid approaches that integrate CNNs and ViTs have shown notable gains in classification and detection accuracy while maintaining efficiency, especially when incorporating knowledge distillation strategies to improve generalization [44]. Furthermore, object detection has benefited from transformer-based models enhanced with attention-guided mechanisms and optimized data distribution schemes, enabling better performance in complex and cluttered scenes [41, 43]. Lightweight ensemble models and robust regularization techniques have also improved classification outcomes, particularly under noisy data or variable acquisition conditions [42, 46]. The use of cross-modal knowledge distillation and feature fusion frameworks has contributed to more discriminative representations, which are critical for real-time ADAS decision-making [46, 40]. These advances not only increase the precision of object recognition systems but also enhance their adaptability to varying environmental conditions. Moreover, conceptual advances in knowledge representation, such as the integration of concept lattice frameworks, provide additional interpretability layers in image understanding [56]. Collectively, these recent contributions underscore the importance of architectural innovation, data correction strategies, and semantic modeling in pushing the boundaries of image-based perception systems for intelligent transportation.

This research in addition to recognizing 4 emotions characterized within the continuous model proposed by Russell (Neutral, Happy, Angry and Sad) using a set of driver behavioral data (steering wheel movement angle and the movement generated in the acceleration and braking pedals), also introduces key optimizations that improve accuracy and efficiency in emotion recognition. Using a temporal segmentation strategy using 50 Hz windows with steps of 5, which allowed preserving relevant features of the driver's behavior without losing data resolution. Likewise, different machine learning algorithms were compared, highlighting the Random Forest model as the most efficient. Compared to previous work focused mainly on physiological signals or facial recognition, this proposal demonstrates that motor behavior analysis can offer a less invasive and sufficiently accurate alternative.

1.1. Related works

Currently, numerous approaches have been proposed for recognizing emotions in drivers, implementing a variety of techniques for data acquisition and processing. This section presents a synthesis of recent relevant works, categorized by the modalities employed in data collection, including visual cues, physiological signals, and multimodal strategies. Visual-based methods, particularly facial expression analysis, have received significant attention due to their non-intrusive nature and suitability for real-time applications. Studies have employed convolutional neural networks, support vector machines, and ensemble learning techniques to achieve high accuracy under varied driving conditions [50, 51, 55, 33, 26, 11, 29, 57, 16, 23]. Similarly, physiological signal-based approachesâleveraging data such as heart rate, electrodermal activity, and EEGâhave demonstrated strong potential for emotion detection, although their practical use is often hindered by intrusiveness [21, 49, 27]. More recently, multimodal frameworks have emerged as a promising direction, integrating visual and physiological signals with behavioral cues to enhance recognition accuracy [12, 37, 61, 28].

Despite these advances, a gap remains in linking emotional recognition directly with driver behavior in context-aware systems. While several studies explore either the internal state of the driver or external manifestations such as fatigue and distraction, few explicitly address how emotional states influence observable driving actions or decisions. Given that emotions can significantly affect reaction time, decision-making, and risk perception, their real-time recognitionâespecially when correlated with behavioral metricsâcould enhance the effectiveness of Advanced Driver Assistance Systems (ADAS). Emerging multimodal approaches suggest a feasible path toward this integration by combining motor behavior analysis with facial and physiological data. However, further research is needed to develop robust models that not only classify emotions accurately but also interpret their influence on driver conduct in dynamic environments.

1.1.1. Visual-based Emotion Recognition

Emotion recognition in drivers has been predominantly studied through visual-based methods, especially facial expression analysis using digital cameras. Verma et al. [50] proposed a real-time system that utilizes a mixture of trees for face detection and VGG16 for feature extraction, achieving over 95 % accuracy under varied environmental conditions. A follow-up study introduced a novel approach based on subspace separation and Grassmann graph embedding for facial expression classification [51]. Wu et al. [55] integrated facial emotion recognition with an audio-on-demand module, using deep convolutional neural networks to proactively mitigate driving risks. Patil et al. [33] employed a Support Vector Machine (SVM) with fused Local Binary Patterns and facial landmarks, attaining 86 % accuracy.

Near-infrared imaging has also been applied to circumvent lighting variability. Naqvi et al. [26] used NIR sensors and CNNs to classify aggressive versus normal driving, achieving 90.5 % accuracy. Du et al. [11] combined facial geometry and heart rate data within a deep learning framework, demonstrating improved accuracy through multimodal fusion. Oh et al. [29] proposed a method for recognizing eight emotional states by fusing Electrodermal Activity (EDA) and facial imagery, reaching an accuracy of 86.8 %. While these video-based approaches offer accessibility and real-time applicability, they are still challenged by head pose variations, occlusions, and identity biases.

Zaman et al. [57] presented a high-performing ensemble classification system that integrates CNNs, RNNs, and MLPs using features extracted via a modified Faster R-CNN and InceptionV3 architecture. Their model achieved outstanding accuracy across multiple datasets, with up to 99.90 % on a custom simulation dataset. Similarly, Jain et al. [16] introduced a bio-inspired optimization technique Squirrel Search Optimization for fine-tuning a NASNet Large and GRU-based facial recognition pipeline, which outperformed baseline models in detecting emotions in autonomous vehicle environments. Monisha et al. [23] also emphasized the role of facial expressions and proposed a real-time machine learning-based framework to address shortcomings in previous classification techniques.

1.1.2. Physiological Signal-based Emotion Recognition

Despite the prevalence of image-based methods, physiological signals offer a complementary and often more objective perspective on emotion recognition. López et al. [21] explored the recognition of basic and complex emotions using eye tracking, biometrics, and EEG measurements. Valenza et al. [49] utilized nonlinear analysis of short heart rate variability (HRV) time series to evaluate emotions in visually induced experiments. Although these methods show strong potential, their intrusive nature can lead to discomfort and bias, limiting real-world applicability.

Ni et al. [27] contributed a multimodal framework for emotion recognition by integrating electrophysiological responses, nasal-tip temperature, and vehicle behavior in a simulated car-following scenario. After signal denoising and factor analysis, Random Forest and other machine learning models were evaluated, with RF yielding the best performance. This study highlights the necessity of combining physiological and behavioral features for robust emotion recognition in intelligent vehicles.

1.1.3. Multimodal and Hybrid Approaches

A growing number of studies now leverage multimodal strategies to improve emotion recognition accuracy and reliability. Espino-Salinas et al. [12] developed a system combining motor activity signals with facial geometry images. Using a pre-trained CNN and a unidimensional neural network, their model achieved 96.0 % accuracy in a simulated environment, demonstrating a strong correlation between motor behavior and emotional state.

Shang et al. [37] took a unique approach by integrating both fatigue and emotion detection into a unified model. Using Dlib for facial landmark extraction, the authors computed fatigue metrics such as PERCLOS and yawn frequency, and applied a lightweight RM-Xception CNN for emotion classification. A composite score derived from time-series fusion of both indicators achieved 73.32 % accuracy, offering a comprehensive assessment of driver state.

Zhang et al. [61] proposed a self-supervised method for distraction detection based on masked image modeling (MIM) and Swin Transformer architectures. By avoiding extensive dataset labeling and optimizing model architecture with attention mechanisms and data augmentation, their system achieved a remarkable 99.60 % accuracy, illustrating the effectiveness of transformer-based models in driver monitoring tasks.

Finally, Oh et al. [28] addressed the challenge of dataset quality by introducing a real-world data acquisition system where drivers self-report emotions via an HMI interface. Over 122 hours of accident-free data were collected, enabling robust, personalized emotion recognition. The study demonstrated the value of self-annotated, real-world data for advancing emotion recognition technologies in context-aware driving systems.

2. Materials and Methods

This section aims to establish the materials and methods to follow as shown in Fig. 1. Generation of a set of behavioral signals in drivers, analysis and processing of the information acquired from drivers in the 4 induced emotional states (Neutral, Happy, Anger and Sadness) for classification using ML algorithms and finally the validation of the different emotion recognition models in drivers using the most used metrics in the area of Artificial Intelligence (AI).

2.1. Emotion induction

Experimental emotion induction provides the strongest evidence for the effects of emotions on psychological and physiological outcomes [39]. In the present study, the augmented autobiographical recall technique was evaluated as a method of emotion induction in a simulated driving environment to collect data related to drivers' behavior in different emotional states.

2.1.1. Virtual environment

The study was conducted using an open-source CARLA 0.9.13 static driving simulator developed to aid the creation, training and validation of autonomous vehicles. CARLA attempts to meet the requirements of several ADAS use cases, i.e., training of perception algorithms or learning of driving policies, CARLA is also free to use, and the sensor suite configurations provide signals that can be used to train driving strategies [48]. In the case of this research, the simulator provides essential elements to meet both technical and safety requirements to successfully conduct the different tests established. The route to follow in the simulated driving environment will be the one that the study subject wants to follow, since the traffic, signaling and environment will be the same for each one.

2.1.2. Continuous dimensional emotion model

Continuous dimensional emotion model it is proposed as a reference for this research work, since the boundaries for distinguishing emotional states are imprecise, the states are said to be continuous without a break point. If emotions were categorized into a dozen discrete types, only the main aspects of the emotion would be shown and the emotional state could not be accurately quantified, not to mention that the discrete model of emotions are not consistent across cultures and nationalities. That is why the present study implements a continuous dimensional method of emotion quantification. The method will use several basic axes orthogonal to each other to show different dimensions of emotion (Li et al., 2022).

The Valence-Arousal emotional quadrant system proposed by Russell (Russell, 1980), which is frequently used in affective computing and it places the different emotions in different quadrants depending on the levels of arousal and valence presented by each person. In this case, four target emotions were established, categorized in three of the four quadrants (quadrant 1 = happiness, quadrant 2 = anger, quadrant 3 = sadness) and 1 located in the initial point of the Cartesian plane (Neutral). Fig. 2 shows the two dimensions in which emotions will be characterized, where the valence level and the arousal level are represented. The values of the valence axis refer to the degrees of happiness and sadness of the subjects of study, on the other hand the values of the arousal axis indicate on the positive side the excitement, while the negative value indicates a state of calmness.

In order to objectively determine that the induced emotional state coincides with the real emotional state of the participants during the driving test, the most widely used and adopted method for assessing continuous emotional states is the Self-Assessment Manikin Scale (SAM) approach. This method is graphically designed by introducing a questionnaire to visually assess the degree of valence and arousal. The questionnaire shows a discrete scale between 1 and 9 as shown in Fig. 3.

2.1.3. Autobiographical recall

However, as an emotion induction technique, the author Braun et al. [4], suggest that autobiographical recall works very well to induce emotions in driving studies and is versatile to use.

The research claim that a significant advantage lies in the fact that the user generates the stimulus himself, which leaves little room for misinterpretation. Active counting can also be performed while driving, allowing for a less abrupt transition from elicitation to the driving task. In summary, autobiographical recall is the first choice for eliciting emotions in driving studies, and music playback can be used to prolong the effect of induced emotions.

Autobiographical recall consists of asking participants to recall and write down past events to remember a specific emotion. Participants are asked to provide details and to report the events. When conducting, participants must tell this story to themselves without the experimenter in the room [18]. Additionally, a song will be played that generates the emotion corresponding to the autobiographical memory established to the study subject throughout the journey, with the intention of extending the emotional effect. The songs were taken from the DEAP database as shown in Table 1. DEAP database [17]. It is a freely available dataset containing EEG, peripheral physiological, and audiovisual recordings made by participants while watching and listening to a set of music videos.

2.2. Data acquisition

The data acquisition process basically consists of collecting the different signals generated by the steering wheel angle, accelerator pedal movement and brake pedal movement of the participants in an emotionally induced state during the driving task in a time span of about 5 minutes per participant.

2.2.1. Registration of data

To obtain the behavior data, a Logitech G29 Driving Force was used as driving peripherals (steering wheel, accelerator pedal and brake pedal) designed for current driving and simulation games, that uses the internal properties of the simulator to store the data required for the research, such as: steering wheel angle and amount of movement generated in the brake and accelerator pedals. The specifications of the central processing unit (CPU) consist of an Intel Core i5-9400F processor at 2.90 GHz, 32 GB of RAM, and a NVIDIA GeForce GTX 1070 Ti graphics card. The following Cuadro. 1 shows the features acquired in the driving process of the study subjects and additionally exemplifies how the data is generated through the experimental testing process.

Cuadro 1: Example of simulator data capture per participant.

Sample	Throttle movement	Brake movement	Steering Wheel Angle
1	0.679931302	0	-0.243051659
2	0.672789414	0	0.301507503
3	0.669198607	0	-0.104604312
⋮	⋮	⋮	⋮
1	0	0.549534057	-1.439965432
2	0	0.392749183	-0.079991518
3	0.524402881	0	-0.590714625
⋮	⋮	⋮	⋮
1	0	0.898714153	2.221737421
2	0.476545161	0	-1.892375448
3	0.402442758	0	3.758628905

On the other hand, Cuadro. 2 shows detailed information about the dataset collected for training the ML models, such as the total number of samples per category.

Cuadro 2: Dataset distribution by emotional category.

Emotion	Total Samples	Training (80 %)	Test (20 %)
Neutral (0)	67,462	53,969	13,493
Happiness (1)	99,148	79,318	19,830
Anger (2)	70,608	56,486	14,122
Sadness (3)	65,408	52,326	13,082
Total	**302,626**	**242,099**	**60,527**

2.3. Data processing

Data processing involves several steps to transform raw data into a format suitable for analysis. These steps typically include data cleansing, data transformation, and data integration. In this case, the data obtained by the CARLA simulator went through a 50 Hz windowing process in steps of 5, so as not to lose important information between window and window that can help identify emotions through the behavior of drivers in the different emotional states. Subsequently, 4 emotion classification models were generated using 4 ML algorithms, these algorithms are detailed below.

2.3.1. Random forest

Random Forest is an ensemble learning algorithm that combines multiple decision trees to make predictions. Each decision tree is constructed using a random subset of the training data and a random subset of features, resulting in a diverse set of individual tree predictions [5](. The final prediction is obtained by aggregating the predictions of all the trees. In this case, the training consists of creating a bootstrap sample Dt by randomly selecting n samples from D with replacement, then training a decision tree Tt using Dt by recursively partitioning the data based on feature splits that optimize a certain criterion (e.g., Gini impurity or information gain) and finally returning the set of decision trees$T_1, T_2, ..., T_T$ to obtain the prediction, all the predictions of the decision trees are aggregated and obtained by equation (1).

$$\widehat{y} = \frac{1}{T}\sum_{t=1}^{T} f_t(x) \tag{1}$$

In Cuadro. 3, the specific hyperparameter settings used for the Random Forest algorithm during the training process are presented. These values were selected to maximize the performance of the model in the task of classifying emotional states from driver behavior.

Cuadro 3: Hyperparameters used in the Random Forest model.

Hyperparameter	**Value**
Number of trees (`n_estimators`)	150
Splitting criterion (`criterion`)	Gini
Maximum depth (`max_depth`)	None (unlimited)
Minimum samples to split a node (`min_samples_split`)	2
Minimum samples per leaf (`min_samples_leaf`)	1
Maximum features per split (`max_features`)	Square root (`sqrt`)
Bootstrap sampling (`bootstrap`)	True
Random seed (`random_state`)	42

2.3.2. Support vector machine

SVM are supervised ML models used for classification that aim to find a hyperplane that separates the data into different classes, thus maximizing the margin between classes. The radial basis function (RBF) is a kernel used to handle non-linearly separable data [58]. The SVMs with RBF kernel can be mathematically described as follows: SVM Training with RBF Kernel: - The SVM with the RBF kernel finds the decision boundary by solving the following optimization problem:

$$\underset{\alpha}{min} = (\frac{1}{2}\sum_{j=1}^{n} \alpha_i \alpha_j y_i y_j K(x_i, x_j) - \alpha_i) \tag{2}$$

In the above equation (3), xi and yi represent the i-th training sample and its corresponding class label, respectively. The kernel function $K\,(x_i,\ x_j)$ computes the similarity between two samples using the RBF kernel of equation (3).

$$K(x_i, x_j) = exp(-y||x_i - x_j||^2) \tag{3}$$

The prediction for a new input feature vector x' is obtained by equation (4):

$$\widehat{y} = sign(\sum_{i=1}^{n} \alpha_i y_i K(x_i x') + b) \tag{4}$$

The specific hyperparameter settings used for the SVM algorithm were as follows: C=250 which controls the level of penalty for classification errors. A high value such as 250 forces the model to make few errors, even if it risks overfitting. gamma=0.001 determines the influence of each training point. A low value like 0.001 generates smoother and more general decision boundaries. Finally, a kernel='rbf' defines the type of function that transforms the data. The RBF kernel allows one to separate nonlinear data in a higher dimensional space.

2.3.3. K-nearest neighbors

KNN works by finding the nearest value to a given data point and making predictions based on the labels or values of those neighbors [60] Given a new input feature vector x', the KNN algorithm performs the following steps for classification, in this case with K = 12: Calculate the distance between x' and all training samples using Equation (5).

$$distance(x', x_i) = \sqrt{\sum_{j=1}^{m}(x'_j - x_{ij})^2} \tag{5}$$

Where x'_j is the jâth feature of x' and x_{ij} is the jâth feature of the iâth training sample. After this approach, the select the K nearest neighbors based on the calculated distances. Determine the majority class among the K nearest neighbors and assign it as the predicted class for x'. The KNN Regression is calculated as follows: Given a new input feature vector x', the KNN algorithm performs the following steps: Calculate the distance between x' and all the training samples as described above. Select the K nearest neighbors according to the distances calculated. Compute the average or weighted average of the output values of the K nearest neighbors and assign it as the predicted value for x'.

The choice of distance metric (e.g., Euclidean distance) and the method for determining the majority class or calculating the mean value may vary depending on the specific implementation and problem domain. In the case of the present study a K=7 was used.

2.3.4. Naive bayes

Naive bayes is a simple yet powerful probabilistic classifier based on applying Bayes theorem with the naive assumption of feature independence. Naive Bayes models are commonly used for classification tasks, especially in natural language processing and text classification [34]. The Naive Bayes Classification is as follows: The Naive Bayes classifier calculates the posterior probability of each class given the input features and selects the class with the highest probability, after that, the posterior probability can be calculated using Bayes theorem shown below in equation (6).

$$\frac{P(Y = C_i) \cdot (X = (x_1, x_2, ..., x_n|Y = C_i)}{P(X = (X = (x_1, x_2, ..., x_n))} \tag{6}$$

Due to the naive assumption of feature independence, the likelihood term can be expressed as the product of individual feature likelihoods:

$$P(x_1|Y = C_i) \cdot P(x_2|Y = C_i) \cdot ... \cdot P(x_n|Y = C_i) \tag{7}$$

The prior probability $P(X = (x_1, x_2, ..., x_n))$ can be ignored during the classification process since it remains constant across all classes and finally, the class with the highest posterior probability is selected as the predicted class for the given input features:

$$\widehat{y} = \underset{ci}{argmax} P(Y = C_i|X = x_1, x_2, ..., x_n) \tag{8}$$

To apply Naive Bayes, the prior probabilities $P\ (Y\ =\ C_i)$ and the likelihoods $P(x_j \mid Y = C_i)$ need to be estimated from the training data, then the prior probability of class C_i can be estimated as the frequency of class C_i in the training data and lastly the likelihood of feature C_i given class C_i can be estimated using different probability distributions based on the type of features. For continuous features, a common choice is to assume a Gaussian distribution, while for discrete features, a multinomial or Bernoulli distribution can be used.

The GaussianNB model used in this study is configured with its default hyperparameters, the most relevant being the smoothing of the var,of the var, whose value is $1e-9$. This parameter adds a small constant to the variance calculated for each class, in order to avoid divisions by zero or extremely small values that could destabilize the model. In addition, by not specifying values for priors, the model automatically estimates the a priori probabilities of each class from the training data. This configuration allows the classifier to assume a normal distribution for each feature, which is appropriate for continuous data such as those used in this work.

2.4. Evaluation Metrics

The validation process of ML algorithms allows to make a numerical representation of the algorithm's performance by being able to see how many predictions of different emotions through behavioral data were correct and incorrect; how accurate or precise the predictions are[14]. In ML, these metrics are commonly summarized in several ways, some of which were applied in this work, such as accuracy. It is one of the most common metrics used in the area of machine learning and is used to determine the performance of models to discriminate between different established categories and consists of dividing all correctly classified observations by the total number of observations [13].

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{9}$$

Where TP, FP, FN are the number of true positives, false positives, false negatives, respectively.

A performance measure of ML-generated classifiers that is widely suggested for classification of unbalanced data is precision and recall. Accuracy measures the proportion of correctly identified emotions among the total number of emotions examined across the processed signals, and recall measures the proportion of signals per participant that were assigned to a given emotion, among the signals that actually belong to a specific emotion [47].

$$precision = \frac{TP}{TP + FP} \tag{10}$$

$$recall = \frac{TP}{TP + FN} \tag{11}$$

Also, the F1 measure is widely used in the area of ML, not only for binary classification cases, but also in multiclass cases. In multiple cases such as the one proposed in this research work, the F1 micro/macro averaging procedure can be used, which can even be oriented toward optimization [20].

$$F_1 = \frac{2}{\frac{1}{precision} + \frac{1}{recall}} = 2 \cdot \frac{precision \cdot recall}{precision + recall} \tag{12}$$

Confusion matrices are a validation metric for evaluating errors in classification problems (the classification of elements into classes, i.e., categories). ML typically applies confusion matrices to inspect errors for each class, encoding the total of classified observations in different cells of the matrix where true positives (TP), false positives (FP), true negatives (TN) and false negatives (FN) are assigned [2].

The receiver operating characteristic (ROC) curve and area under the curve (AUC) is a performance measure for classification problems. ROC is a probability curve and AUC represents the degree or measure of separability between two classes. Indicates how much the model is able to distinguish between two classes. The higher the AUC, the better the model is at predicting dichotomous values (0 and 1). In short, the higher the AUC, the better the model will be at distinguishing between two different classes. The ROC curve is plotted in a two-dimensional plane with the true positive rate (TPR) on the "Y.ªxis versus the true negative rate (FPR) on the "X.ªxis [35]. On the other hand, the AUC is formally represented as shown in the following equation.

$$AUC = \sum_i (1 - \beta_i \bullet \Delta\alpha) + \frac{1}{2}[\Delta(1 - \beta) \bullet \Delta\alpha] \tag{13}$$

Where $\Delta(1-\beta) = (1-\beta_i) - (1+\beta_{i-1})$ y $\Delta\alpha = \alpha_i + \alpha_{i-1}$

Although the AUC/ROC is widely used as a metric to validate binary classification models, there is the .ºne vs all”strategy that is used to see the behavior of multiclass models, as is the case in this work, where there are four classes. (4 emotions) Neutral, Happy, Angry and Sad, then N numbers of curves can be drawn for N classes, you will have Neutral against happy, angry and sad, another for Happy classified against neutral, angry and sad, and so on for each category.

3. Results

This section presents the results obtained in each section of the proposed methodology. First, 50 induction tests of 4 emotions were carried out during the driving process on 50 participants between 18 and 39 years old with a minimum of one year of driving experience, all of them university students. Initially, each of the study subjects went through a process of neutralization of emotions implementing the same method of autobiographical memory is the first choice to elicit emotions in driving studies and music playback can be used to prolong the effect of induced emotions (Braun et al., 2018). At the end of the test driving, each participant marked their emotional state during the test using the SAM to identify their levels of arousal and valence with the purpose of identifying them within the two-dimensional plane of the continuous model as shown in Figure 4. in order to that the induced emotion coincided with the real emotion reflected in the SAM. Since according to Oh et al [29]. Regardless of the method used for the induction of emotions, it must be considered that the desired emotion and the real emotion are the same.

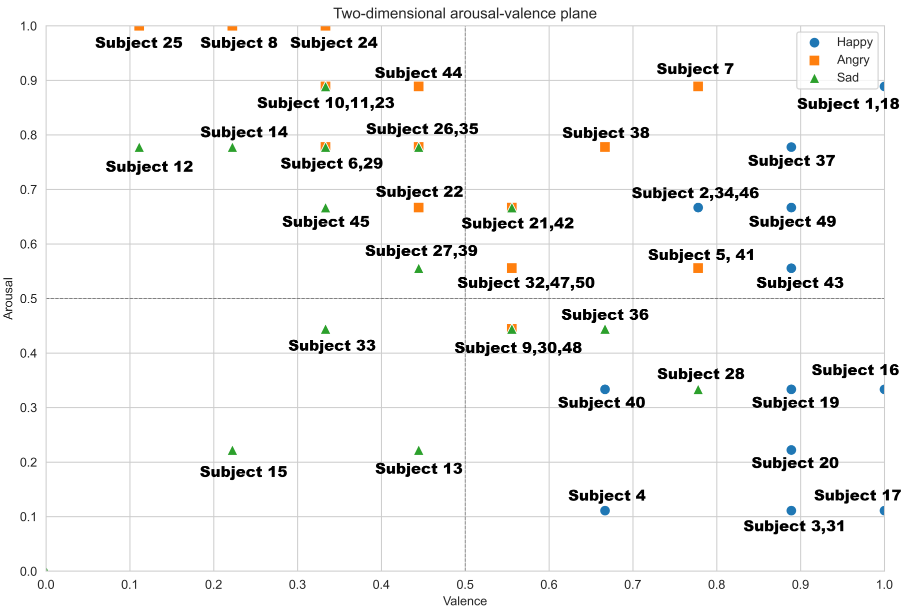

Figura 4: Characterization of emotions in the continuous model of study subjects during induction tests in a simulated driving environment [12].

The graphic illustrates the distribution among the 50 participants, revealing that only 42 % of them experienced an induced emotion consistent with their actual emotional state. This corresponds to 21 individuals in total, with 9 exhibiting happiness, 9 displaying anger, and 3 expressing sadness. Notably, the remaining 58 % of participants demonstrated no correlation between the induced emotion and their real emotional state. For participants with neutral emotions, those aligning with a neutral emotion during the emotion neutralization phase were included, totaling 4 individuals. Ultimately, only the data from the 25 participants whose emotions were accurately validated underwent processing for their driving behavior.

From the 25 participants, 302,626 motor data and 3 characteristics related to the angle of the steering wheel and movement of the accelerator and brake were collected for each of the 4 induced emotions.

Figure 5 shows the behavior of the steering wheel angle signal in the different emotional states during the driving tests.

Figura 5: Steering wheel angle signal in different emotional states.

To identify a behavior related to the different target emotions established in this study, it is necessary to define data windows that are sufficiently robust that they can offer significant information. For this, it was necessary to define 50 Hz windows every 5 steps and process them using machine learning algorithms. in order to obtain models that classify the emotions of Nuetro, Happy, Anger and Sad with a statistically significant index that exceeds more than 50 % for. With this, in addition to finding the signals that are directly related to each of the emotional states, we could also obtain a first approximation to models capable of objectively identifying emotions with high precision. The results of each of the implemented algorithms are shown in Cuadro 4. where the final data set consists of 60,516 samples for 150 motor data in 4 different emotional states, this new dimensionality of the data set is due to the fact that the selected windows reduce each participant's motor samples to expand the data range per second for each driver. Of the 60,516 samples that make up the data set, 80 %, equivalent to 48,412 samples, were used to train the algorithm, and the remaining 20 %, equivalent to 12,104 samples, were used for blind testing.

Cuadro 4: Results of validation metrics for ML models.

ML Algorithm	Emotions	Precision	Recall	F1-Score
Random Forest	Neutral	0.80	0.76	0.78
	Happy	0.77	0.80	0.78
	Angry	0.74	0.75	0.75
	Sad	0.74	0.75	0.75
Accuracy				**0.78**
KNN	Neutral	0.59	0.66	0.62
	Happy	0.62	0.66	0.64
	Angry	0.66	0.58	0.62
	Sad	0.59	0.54	0.56
Accuracy				**0.61**
Support vector machine	Neutral	0.46	0.24	0.32
	Happy	0.41	0.65	0.50
	Angry	0.56	0.45	0.50
	Sad	0.44	0.35	0.39
Accuracy				**0.45**
Naive bayes	Neutral	0.46	0.24	0.32
	Happy	0.41	0.65	0.50
	Angry	0.56	0.45	0.50
	Sad	0.44	0.35	0.39
Accuracy				**0.45**

From the results obtained, the RF algorithm obtains the best performance to identify the multiple defined emotions, with 78 % accuracy of the test set. In addition to this result, it can also be highlighted that not all the signals collected from the drivers present information that can reveal their emotional state but only a certain percentage which is based on the values assumed in the validation metrics by the model generated by the algorithm.

On the other hand, it is necessary to know the performance of the RF algorithm to discriminate the signals independently in relation to the others, implementing the .°ne vs All"strategy, this strategy instead of directly addressing the classification problem with multiple classes, which decomposes into several simpler binary classification problems. Figure 6 shows the ROC Curve and the AUC obtained for each classification of each of the emotions.

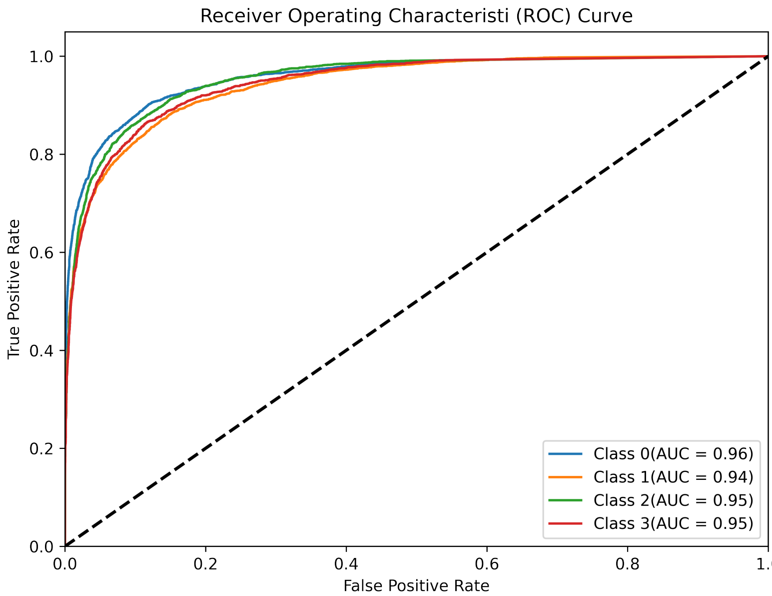

Figura 6: ROC and AUC curves obtained from .ºne vs all”strategy for the different emotions.

The results show that there is indeed a relationship between the behavior of drivers and the different emotional states and that these can be identified, thus having a starting point to find systems capable of performing this type of tasks in a less invasive way.

4. Discussion

The methodology proposed in this study demonstrates the viability of ML models for emotion recognition, based on data related to motor activity or human behavior in a simulated environment. However, there are several works that propose different approaches to emotion recognition in drivers by processing information that does not involve facial geometry images, as shown in Table 3, which provide great advances in this area.

Cuadro 5: Example of simulator data capture per participant.

Author	Data source	Algorithm	Accuracy
Shafaei et al. 2019 [36]	Vehicle patterns and facial geometry	SVM	94.0 %
Wang et al. 2020 [52]	ECG signals	ANN	91.1 %
Du et al. 2021 [10]	Hearth Rate and Facial Geometry	CNN	84.32 %
Oh et al. 2021 [30]	Electrodermal Activity and Facial Geometry	CNN	86.8 %
Mou et al. 2023 [24]	Data of Eye, Vehicle, and Environment	CNN	94.0 %
Hieida et al. 2023 [15]	ECG, EDA and EEG Signals	S-LR	67.0 %

The table above shows the performance of the study of different physiological signals that demonstrate that it is possible to create models capable of recognizing emotions from drivers' own parameters that are not recognizable with methodologies based on computer vision or digital image processing. However, some of these works still require the integration of facial geometry analysis with physiological data to obtain the true potential of an objective model of emotion recognition in drivers, which still implies time and processing power to monitor emotional states. On the other hand, work that relies only on physiological signals such as heart rate or electromagnetic brain impulses is very invasive and can lead to some degree of bias in emotion identification, even in a controlled experimental setting.

In the case of studies based on information related to the behavior of drivers acquired through interaction with the vehicle's peripherals and driving parameters, they have demonstrated a great capacity to identify emotions, although image-based models demonstrate better performance. In each related work the authors implement different models such as: Support Vector Machines (SVM), Sparse Logistic Regression (S-LR), Artificial Neural Networks (ANN) and Convolutional Neural Networks (CNN), showing top accuracy (Every model except the S-LR showed over 84 %). These still face different noise problems, if these are implemented in a real environment where light variations, occlusions and obstructions tend to be the biggest challenge and this is where the development of multimodal emotion recognition models should be considered. as a viable solution given the results obtained.

5. Conclusion

The methodology proposed in this study allowed the analysis of different ML models for emotion recognition through human behavioral or motor activity data. The effectiveness of the generated models was evaluated by different validation metrics for each of the emotions, but focusing on the accuracy of each one, the Random Forest model showed the highest metrics.

A novel contribution of this study is the creation of a database of driver behavior that induces specific emotions, with the goal of characterizing subjects in a two-dimensional Valence-Arousal plane of the continuous model. This will be made available for free use by the research community. In addition, an initial scientific perspective on the connection between drivers' behavior and emotions in a continuous model is offered.

As future work, we propose the use of genetic algorithms for the selection of the most representative features, in order to resize the database. We will also continue with tests within the static driving simulator CARLA 0.9.13 and expand the database. In addition, we will investigate the possibility of adding image capture of the drivers and perform image processing to see the relationship of facial gestures with emotions.

Acknowledgements

This is the place for acknowledgements.

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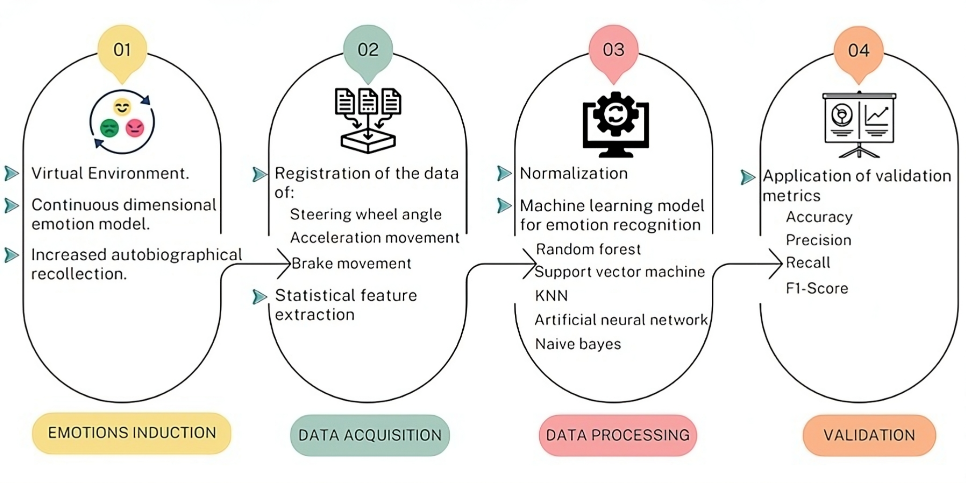

Figura 1: Flowchart of the methodology proposed for emotion recognition using statistical features of driver behavior.

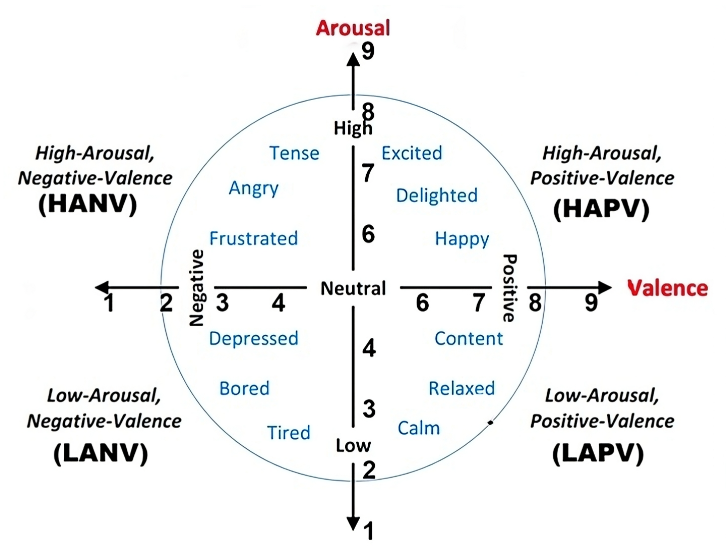

Figura 2: Two-dimensional Valence-Arousal plane of the continuous model of emotional characterization.

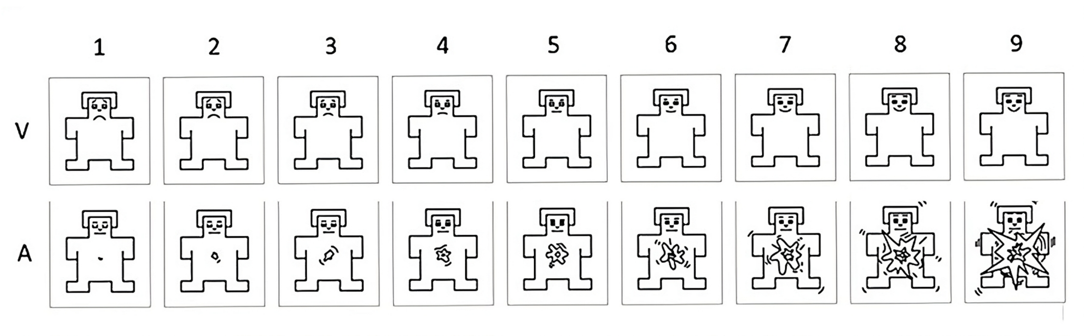

Figura 3: Two-dimensional Valence-Arousal plane of the continuous model of emotional characterization.