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The Creation of Real-Time Emotion Recognition System Following the Machine Learning Algorithm for SmartTransportation

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Abstract

Human emotions and behavior are important factors that impact driving safety. To address the issue of emotional instability in driving, an algorithm was developed to identify human emotions. The study involved data collection from 20 volunteers, and the obtained data was compared with trained data to evaluate the effectiveness of the algorithm. The results indicated a high level of precision and accuracy of the proposed algorithm in recognizing three primary emotions: happiness, sadness, and anger. The accuracy and precision of the algorithm were measured using aconfusion matrix approach, which compared the expected and confirmed readings of the system for each emotion. This study provides a foundation for further research to expand the range of emotions that can be detected and to improve the accuracy of the system. Future research could also explore the use of additional data processing techniques and more comprehensive datasets to enhance the system's effectiveness. The development of such systems can help mitigate the risk ofaccidents caused by emotional driving and improve road safety.

Keywords: emotion, machine learning, distracted driving

1. Introduction

Emotions denote the strong sentiments that influence the environment and become a crucial part of life, decision-making, thought processes, focus, innovation, comprehension, consciousness, preparedness, and reasoning, which contribute to the recognition of feelings for areas of study. The translation of emotion recognition could take place via audio, text, visual, and facial expressions (Suchitra & Tripathi, 2016). Past research works demonstrated that feelings strongly impact individuals' awareness and security (Fauzan, 2019; O'Connor et al, 2019). In another research, emotions were identified as the condition of awareness represented by significant cerebral action and a strong fulfillment or dissatisfaction. There are several manners through which individuals reveal their feelings: facial expression, voice, and body gestures (Keshari & Palaniswamy, 2019). Furthermore, the development of human-car interaction has currently been gaining increasing attention.

Although the consciousness of drunk driving has been present, it is not the case for feelings. The emergence of intense feelings upon traveling by car potentially strengthens the possibility of accidents. Based on emerging research works by the Transportation Institutes of Virginia Tech, emotional driving that involves feelings of sadness, frustration, or irritation causes accident risk by nearly tenfold. It was suggested that impaired driving potentially leadsto a higher risk of the car crashing and emotional driving. Even so, it was found that drivers who were involved in these conducts would experience distraction to their attention for approximately half the period (Dooley, 2016).

Emotional considerations are required in traveling by car to achieve improvement in comfort and security, while the driver's feelings should be identified. These considerations are made to assist the driver with primary, secondary, and tertiary driving actions (activities) in car. The primary actions in driving consist of accelerating, braking, turning, and choosing the right lane, distance, direction, and route for other cars. The secondary driving actions are associated with protection tasks that include running windscreen wiper systems, switching gears and blinking, dimming, and entering, followed by tertiary driving tasks that are associated with seat heating and air conditioning among others (Eyben et al, 2010).

According to the statistics in 2019, car crashes in the US that reached 94% were attributed to driver neglect, increased tiredness, and distraction. Driving safety experts collected crash collection data from over 3,500 vehicles within three years to elaborate on the factors of these types of crashes. Subsequently, more than 1,600 incidents were recorded, which ranged from mild accidents including contact with a curb to severe accidents that require legal action.

From 1,600 accidents, 905 accidents were recorded as severe to the point of causing accidents or collateral harm, while approximately 90% of accidents were clearly classified as driver error, tiredness, disability, and distraction (Gartland, 2019).

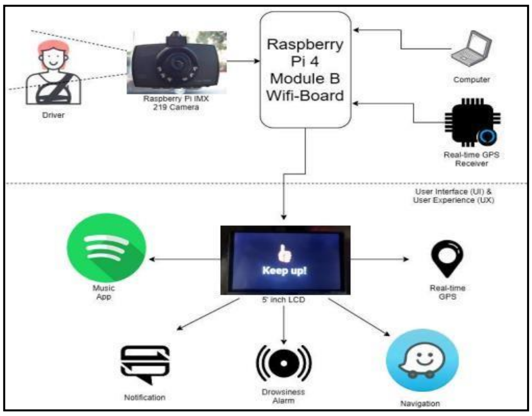
Another element may originate from the viewpoint of human factors contributing to road accidents. Human elements could be the cognitive, physical drivers, and emotional attributes that could lead to driving patterns. In relation to this, attributes could fall under the category of tiredness, viewpoint, encouragement, features, and emotional condition. Therefore, emphasis is required on the factors for a driver's need for positive feelings upon traveling by car as it can cause potential accidents that are damaging (Pêcher et al. 2015). Furthermore, feelings may consist of aggressiveness, anger, tiredness, pressure, sleepiness, confusion, anxiety, sadness, and lack of attention. Overall, all these conditions could impact driving conducts and the driver's thinking, and possibly lead to accidents. Past studies described that driver's confusion could also lead to lower decision-making capability (Weber, 2018). Negative feelings could strongly impact driving ability and lead to traffic injuries and crashes.

2. Methodology

2.1 Creation of Facial Recognition System

In order to train the facial recognition algorithm for emotion detection, a large dataset of facial images representing different emotional states was collected and labeled. The image processing procedure involved several steps, such as face detection, alignment, and feature extraction using techniques such as Haar cascades and deep neural networks. The employed machine learning algorithms included convolutional neural networks (CNNs) and support vector machines (SVMs) for classification. The CNNs were trained using the collected dataset to learn discriminative representations of facial features that correspond to different emotional states. The SVMs were then used to classify the extracted features into the three different emotions of sadness, happiness, and anger. The resulting algorithm was tested on a separate set of images to evaluate its accuracy and performance. The entire process is illustrated in Fig. 1.

Figure 1: Block representation of the project element and integration system between the driver and car description



The innovative technology integrated into this smart device enables it to accurately detect human emotions while driving by measuring the eyes' aspect ratio and developing a sophisticated algorithm for facial recognition. With seamless connectivity to the vehicle's GPS, the system discreetly scans the driver's face at intervals of 20 minutes, allowing for real-time analysis and feedback. Conveniently, this cutting-edge system provides interactive access to music apps and navigation, while a front-facing camera continually monitors facial changes that are then displayed on the screen with customizable suggestions based on the driver's current emotional state. With the freedom to select a preferred solution, drivers can create a personalized driving experience that is both responsive and intuitive. The entire process is illustrated in Fig. 1.

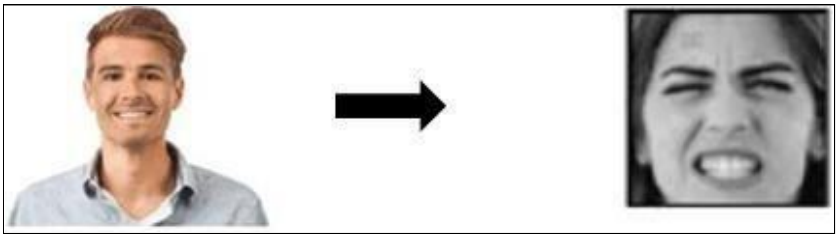
Facial attributes such as expression and emotion can be effectively used to identify an individual's feelings. However, in the process of identifying these attributes, there is a risk of reduced motion recognition precision when the initial step of processing involves cropping the region of both eyes. To address this issue, Haar-Cascades has been employed as an additional algorithm to enhance precision detection (Yang et all, 2018). This approach includes computing a variety of variables for detecting mouth characteristics, which significantly improves object identification. The Haar-Cascade-based object identification method is highly effective as it uses machine learning algorithms to perform training on a cascade function derived from a large number of favorable and adverse images. This approach involves training on a set of images to recognize particular characteristics and enables identification of objects in other images with similar characteristics. (Mordvintsev, 2020).

Overall, the approach involves a combination of machine learning algorithms and procedures aimed at enhancing image processing and identifying facial attributes with high precision, as seen in Fig.2

Figure 2: Facial analysis point applied in identifying feelings through facial expression representation of the project element and integration system between the driver and car description

Data processing techniques such as grayscale approaches were employed in this study to improve the recognition precision of emotion identification from 200 JPEG formatted image files. The quantity of saved images was also found to impact the precision. Prior to using the data samples as a dataset for machine learning, pre-processing actions such as inversion and cropping were not required as they only increased the precision of the pre-training model. While a black-and-white image with RGB pixel values could be described, identifying the grayscale pictures is simpler and more effective. However, colored images could not be indicated through the use of grayscale pixels due to their inability to capture a single hue of the pixels, as illustrated in Figs. 3a and b.

Figure 3: Facial Figures 3a. Original data without cropping, and; 3b. Inverted and cropped to greyscale



Data teaching algorithms are powerful tools that enable the development of knowledge, foster partnerships, and support effective decision-making. These algorithms achieve such impressive results by actively collecting training information and identifying patterns that highlight the loyalty of the system. The efficacy of the model is heavily reliant on the number of training data, as this factor ultimately determines the accuracy and reliability of the algorithm. Thus, it is clear that training data consistency and quantity have a direct impact on the success of a data project that incorporates algorithms.

2.2 Volunteers Demographic

A group of 20 university students with 23.0±1.3 years mean age was involved as volunteers. Their height was within the range of 168.2± 4.0 cm with the weight ranging within 64.2±12.2 kg. Furthermore, all the volunteers' vision and hearing were regular. They were required to fulfil the pre-screening requirements that do not include history back pain or neck injury and should not be on medications or drugs. However, they were restricted from the intake of any caffeine and medicine and should obtain adequate sleep (8 h) prior to the experiment.

2.3 Ethical Consideration

Verbal and written explanations were presented to the respondents regarding the objective of the experiment. Every respondent had the freedom for refusing their involvement in the experiment, and the confidentiality of the findings was kept.

Following the processes of the investigation, the written form of permission was acquired from the entire volunteers.

2.4 Image Processing and Validation

Python 3.8 platform with OpenCV 4.5 library was selected to process the images. TheOpenCV 4.5 consists of the variable function that facilitates the transfer of the figure. The computer vision procedure could be mitigated through the import of the OpenCV library. The OpenCV library approach is employed particularly for the detection of articulated data and objects. In comparison to the suggested approach, the precision of the original dataset could be computed with the use of 200 data samples as machine learning pre-train model dataset. The original dataset was directly fed to machine learning, while the suggested approach cleaned and filtered the dataset prior to transferring it for machine learning.

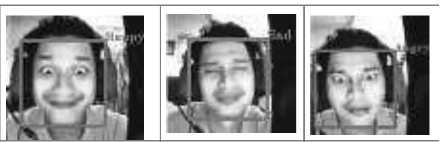
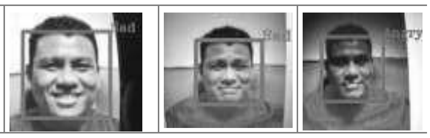
The dataset in the suggested approach would solely perform cropping on the faces, followed by conversion into grayscale images to ensure that a comprehensible reading for Facial Action Coding System (FACS) was obtained.

3. Results

3.1 Human Emotion Detection

The results describe the output of an emotion identification system that was tested on 20 university student volunteers. The age information did not impact the system's performance, indicating that the system was accurate in identifying emotions across different age groups.
The dataset used to train the AI machine learning algorithm comprised a large amount of data that included distinctions in terms of gender, age, and race. This suggests that the AI model wastrained on a diverse dataset, making it capable of accurately identifying emotions in different populations.
Table 1 presents the results of the emotion identification system, and the statement notes that the evaluation was conducted using a confusion matrix approach to calculate the average precision of identifying three emotions: anger, sadness, and happiness. The confusion matrix approach is a suitable method for calculating image precision, and it is commonly used in evaluating theperformance of image classification models. The statement explains that the accuracy or flaw occurring in the system would be compared to achieve value precision and effectiveness of the system that processes the image. This means that the confusion matrix approach was used to evaluate the accuracy and effectiveness of the emotion identification system in processing and classifying emotions.
Overall, the results provide important information about the methodology and results of the study, which could be useful for researchers interested in emotion identification systems and AI machinelearning algorithms. The findings suggest that the emotion identification system was accurate in identifying emotions across different age groups, indicating its potential usefulness in various settings, such as mental health diagnosis, customer service, and entertainment industries.

Table 1: Human emotion identification for 20 volunteers

Voluntee r1		Voluntee r6	
Voluntee r2		Voluntee r7	
Voluntee r3		Voluntee r8	
Voluntee r4		Voluntee r9	
Voluntee r5		Voluntee r10	

3.2 Confusion Matrix

The confusion matrix describes the results of a study that compared the effectiveness and precision of a present solution and a suggested approach for identifying emotions in images. Tables 2 and 3 present the findings of the study, which evaluated the performance of the two approaches across three emotions: happiness, sadness, and anger.

The study incorporated two groups of information, and every data point was employed in three separate expressions, resulting in a total of 200 image data being analyzed. The findings of the study highlight the contrasts in effectiveness and precision between the present solution and the suggested approach, indicating the potential benefits of using the suggested approach for emotion identification.

Table 2: Confusion matrix data computation for the original dataset

		Predicted			
		Happy	Sad	Angry	Total
Actual	Happy	166	24	10	200
	Sad	13	158	29	200
	Angry	7	17	176	200
	Total	186	199	215	600

Table 3: Confusion matrix data computation for the suggested dataset

		Predicted			
		Happy	Sad	Angry	Total
Actual	Happy	176	15	9	200
	Sad	12	170	18	200
	Angry	5	9	186	200
	Total	193	194	213	600

3.3 Data Accuracy

The statement highlights the findings from Tables 4 and 5, which illustrate the results of two groups of information from diverse outputs. The output was separated based on the quantity of each dataset for every expression, resulting in a total of 200 data points. The findings demonstrate the ratio of expected and confirmed readings of each dataset for every expression in percentage.

Table 5 provides information on the accuracy of the emotion identification system for the three expressions: happy, sad, and angry. The table shows that the happy expression has the highest accuracy rate, followed by sad and angry expressions.

This suggests that the proposed algorithm for emotion identification is accurate and capable of identifying happy expressions with high precision.

TABLE 4: The precision for the original dataset acquired from confusion matrix

Emotion	Accuracy (%)
Happy	83
Sad	79
Angry	88

TABLE 5: The precision for the suggested dataset acquired from confusion matrix

Emotion	Accuracy (%)
Happy	88
Sad	95
Angry	93

4. Conclusion

The conclusion of the study highlights the effectiveness of the proposed algorithm for real-time emotion recognition using virtual markers and optical flow algorithm. The algorithm was designed to establish a real-time emotion recognition system that is not computationally complex and can help reduce car accidents caused by emotional driving. The system is effective in human head rotation, irregular lighting, diverse backgrounds, and a wide range of skin tones.

The proposed system is capable of recognizing three primary feelings immediately for facial landmarks, offers a wide range of resolutions for the driver based on their preference, and is accessible. This can help improve the exchange between machines and people and create a more dynamic interaction between the driver and the car.

The study found that the system was capable of recognizing various feelings with an average precision of 93% for angry expressions, 88% for happy expressions, and 85% for sad expressions. However, the study also acknowledges the limitations of the research, such as the focus on only three primary feelings: happiness, sadness, and anger. Future research could explore a wider range of emotions, such as pressure, anxiety, andalarm. The study also suggests that the system accuracy could be enhanced through the increase indata collection and the use of diverse methods for the extraction of more characteristics from Facial Action Coding System (FACS).

Overall, the study provides important insights into the development of real-time emotion recognition systems that can be used to improve road safety and create a more interactive driving experience. The findings of the study could be useful for researchers, developers, and policymakers interested in improving the accuracy and effectiveness of emotion recognition systems and creating safer roads.

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