Intelligent System for Detecting Drowsiness and Stress with Personalized Music Suggestions

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Abstract: ***Unfortunately, car driving has become an inseparable part of millions of people's life experience in the modern, fast-developing world. Although, the stress and weariness resulting from having to manoeuvre through traffic congestion, road hurdles, and long trip (s) (e.g., 18 wheelers truck drivers) affect driver's health. To begin with, we have developed a brand-new system called AI Driven Drowsiness and Stress Detection with Automatic Music Recommendation that can analyse fatigue and stress levels in the drivers in real time. Through data collected from diverse sources including heart rate, skin temperature and face expressions the system effectively measures the wellbeing of the driver. Using such data, it offers specific treatments like giving Music suggestions for removing stress, combating drowsiness, & improving safety & comfort of Drivers for long drives.***

Keywords: Stress, Photoplethysmography (PPG), Electrocardiogram (ECG), Convolutional Neural Network (CNN), Accelerometer (ACC), Blood Volume Pulse (BVP), Electrodermal Activity (EDA), Body Temperature (TEMP), Wearable Stress and Affect Detection (WESAD), Eye Aspect Ratio (EAR), Facial Expression Recognition (FER)

1. Introduction

Driving, it is one of the common daily activities among the population presents considerable risks related to driver's stress and **[1]** fatigue that cause accidents. To effectively respond to such severe problems, we present an AI-based system called "AI-based Drowsiness and Stress Detection with Automatic Music Recommendation". It was designed to improve roads' safety by indicating signs of drivers' drowsiness and stress, giving recommendations for how to adjust driving settings for the more pleasant and safe experience.

Using cutting edge artificial intelligence technology, the driver's key physiological data, including **[2]** facial expressions, heart rate, and skin temperature, which are both stress and fatigue indicators, all monitored. The system uses these real time inputs to accurately detect when the driver has enough stress or has become drowsy and gives these drivers appropriate warning. The system also issues warnings and recommends personalized music playlists intended to both reduce the drivers' stress and to keep them alert, based on the state detected.

The goal of both AI Driven Drowsiness and Stress Detection system is to promote driver well-being as well as reduce risk of accidents from stress and fatigue. The system hopes to greatly reduce accident rates, especially for drivers taking long trips or who drive under stressful conditions, by addressing these issues in real time.

In this paper, we build a comprehensive view of the system working, the AI techniques and methodologies used in the stress and drowsiness detection, and the design process for developing the system. Also, we will also highlight the importance of stress and fatigue managing while driving and how this system can help achieving higher road safety and improvement of overall driving experience.

Our present-day goal is to bring about decrease of lethal road accidents by providing the driver with an intelligent assistant that will be able to detect fatigue stress and suggest ways on how to handle it on real time basis. This way instead of forcing people to listen to our clever music selection which may help them avoid an accident we plan to easily provide them with a solution that should make their trips safer and more entertaining. Going further, this work can influence the daily driving to the extent that people's daily commutes can be both safer and happier. It is our expected that this outline of our system will encourage the development of further AI safety technologies in the area of road transport.

2. Literature Survey

These aspects of machine learning are mentioned and analysed in the study, [1] and highlight how driver fatigue and drowsiness can be minimized and overall road safety increased through their elimination. Pictures are thus taken from another live webcam feed and machine learning is used on images and then figuring out whether the driver is sleepy. It includes features such as yawning, sleepy eyes as the signals of the program where facial expressions and the movements of the body are used. Based on landmarks of the eyes, the EAR calculates the horizontal and vertical distances in order to determine the degree of tiredness. Additionally, the system measures driver drowsiness level using three different criteria: that is the blinking rate, the time the eyes are closed, and yawning. If the value goes beyond this threshold, then it is audible to the driver. A group of researchers **[2]** created a smart computer program that can tell how stressed a driver is. They taught the program by using information from twenty different drivers who were driving in different situations. They looked at things like the driver's body signals (like heart rate and sweating), how the car was moving, and the driver's facial expressions. This computer program is called a "multimodal deep learning model" and is like a smart computer. It was trained to say if a driver's stress is low, medium, or high. The computer program got it right 93.2% of the time, which is much better than older methods that were only right 70% to 80% of the time. It is also better at ignoring distractions and other things that could mess up its judgment. This paper **[3]** presents a user-friendly online book recommendation system based on collaborative filtering. Users register, choose their favourite book genres, and rate books to get recommendations. A user survey revealed an 89% satisfaction rate with the recommenda1tions. However, some users faced issues like repeated suggestions and closely related book genres. In summary, the system offers speedy and relevant book recommendations, simplifying the process for readers. This paper **[4]** introduces an audio book recommendation system using open source data. Users can create bookshelves, share them, and access audio summaries of books. The system uses collaborative filtering and content-based recommendations. It suggests improvements for data security and algorithm enhancements in future work. We can improve this system by training model using efficient algorithm to maximize driver experience. This research **[5]** focuses on creating a smart background music system using deep learning and IoT tech for Intelligent Homes. They introduce a feature extraction method that is great for recognizing indoor scenarios, achieving an 87.6% success rate. They also combine various technologies to improve feature extraction. The system works well, but there's room for further IoT exploration and improving network compatibility. This paper provides insights into using IoT devices for music recommendations, and it suggests that we can expand on this idea to enhance the user experience in our recommendation system. They **[6]** propose a machine learning based method for stress detection in automobile drivers from ECG signals. Heart rate segments were extracted from the ECG signal and included heart rate, heart rate variability and spectral features. Subsequently, they trained a machine learning algorithm to predict stress levels by feeding extracted features into it. The proposed machine learning model achieved an accuracy of 88.24% in detecting three classes of stress: low, medium, and high. The accuracy of the proposed method is higher than that of traditional stress detection methods, such as heart rate monitoring. We also found that the model is robust to noise and other interfering factors. A group of researchers **[7]** came up with a smart computer method to figure out if a driver is feeling stressed, and they did it without needing to attach anything to the driver's body. They looked at some body signals like the heart rate and how the heart rate changes, and they also looked at how a person breathes. Then, they taught a computer program to guess how stressed the driver was using this information. The best computer program they tried was called "Random Forest Algorithm," and it did a really good job. It was right 98.24% of the time when it had to decide if the driver was feeling low, medium, or high stress. This is much better than older methods like just checking the heart rate. The computer program was also good at ignoring things that could make it hard to tell if someone was stressed or not. This research paper **[8]** proposes the way of if a driver is feeling stressful by using computers. Using special cameras that detect heat, and sensors placed on the driver's skin, they did this. So, they had data from ten people driving in a pretend car. So, they watched the heat patterns on the drivers faces like nose and forehead and taught a computer program how to tell if someone was stressed just from skin sensors. With an 81% accuracy, the computer program was able to tell whether the drivers were or were not stressed. That is exciting for me, because it means we might be able to build a system to monitor a driver's stress, without having to strap things to their skin. In this paper study, [9], an emotion recognition framework that can be introduced to improve music recommendation systems based on the physiological signal is introduced. Music preference is guided by emotions and this research categorizes emotions from the galvanic skin response (GSR) and photoplethysmography (PPG) readings of wearable sensors. Separate GSR and PPG signals of predictive accuracy on anticipation of arousal and valence are promising and the combination of them slightly improved the results. Furthermore, this framework presents interesting potential for improving music recommendation engines by incorporating multi modal emotional information. Further performance and user experience can be improved through future work with different sensor combinations and sensor failures. In this research paper we talk about using emotions for music recommendations, but we can extend upon this feature by adding driver stress detection. This integration will even allow us to recommend the travel, Audio or Music playlist based on the driver emotional state. This system **[10]** is like a program that can look at your face through your computer's camera. It is trained to figure out what emotion you are showing on your face. When it looks at your face, it gives a score for seven different emotions like anger, happiness, and sadness. The one with the highest score tells the system how stressed you might be. The system can recognize seven facial expressions in total: anger, disgust, fear, happiness, neutral, sadness, and surprise. This paper discusses a new Facial Expression Recognition (FER) system **[11]** that uses hierarchical deep learning. It uses the SoftMax function and a technique to generate facial images using neural emotion using the auto encoder technique. The approaches used here are feature-based and geometric-based methods. The goal of this project **[12]** is to create a system that can tell how stressed a person is by measuring their heart rate, sweat level, and skin temperature. We use a type of computer logic called "fuzzy logic" to give results that are accurate to the user. It addresses the problem of **[13]** driver drowsiness and suggests a system to detect drowsiness in a driver and alert him or her to potential danger. The webcam would capture images of the driver's face, and machine learning algorithms would be applied to these images to determine whether the driver is drowsy or not. It produces an alarm if the driver is drowsy and alerts their family members through text or email messages. Now, let me present the architecture, methodology, and evaluation of the paper. The evaluation results describe how it correctly detects drowsiness in most instances while at the same time discussing its restraints and possible improvements. The paper survey of **[14]** new directions in driver drowsiness detection systems, comprising an overview of the different methods applied to detect driver drowsiness: EEG, EOG and video-based methods. Discussions about the challenges, or limitations, of such methodologies and future research directions are also included. The paper concludes that the detection of drowsy drivers is a complicated task, and one single method cannot work well in real-life situations. Thus, research should be carried out in developing more precise and reliable methods of detecting the drowsiness of drivers by trying to apply them in real-world applications. In this paper, the author goes through **[15]** a tour de force on the driver drowsiness-detection system, with an emphasis on image processing techniques. The paper defined the problem of drowsy driving and its potential effects, highlighted with emphasis the need for developing effective countermeasures. It reviews various methodologies proposed for the detection of drowsiness in the driver - physiological approaches, that is, EEG and EOG, behavioural methods, such as steering wheel movements and lane deviations, and image-based methods. The article then focuses on the designing of an image-based drowsiness detection system during the study. The system captures images of the driver's face using a camera; these are later processed using algorithms in image processing to extract relevant features detected from these images. These features are then analysed for determining the level of drowsiness by the driver. The article discusses specifically the algorithms adapted for feature extraction and classification. In addition, it presents the evaluation methodology selected to assess its performance. Successful results from the study assure that the drowsiness detection system based on images can be very effective. Thus, such a system with high accuracy could be put into real-world application. Again, though, the article also points out limitations with the study and calls for further research to overcome the limitations and improve the efficiency of the system. The paper is about the **[16]** research one concerning the detection of driver distraction. It develops a novel deep learning model namely E2DR. It is, in fact, an ensemble of two deep models: CNN, and RNN. The work applies the E2DR model for the detection of driver distraction from images of the driver's face and body. The paper further provides a recommendation system that informs the driver which actions to undertake to avoid distraction. This was developed based on detected driver distraction and driving context. There was an evaluation of the E2DR model on a set of images for driver distraction. The results came with the demonstration of how the E2DR model surpassed other state-of-the-art models in the detection of driver distraction. There was also discussion and evaluation of the recommendation system. The results showed that it could generate adequate recommendations to drivers. The paper discusses **[17]** the problem of drowsy drivers and offers a system whereby the driver has the real possibility of knowing when he or she is falling asleep and alert to the danger. The system employs a webcam that captures images of the driver's face and applies machine learning algorithms on the same to determine whether the driver is drowsy. It sounds an alarm and sends an SMS or an email to the family members when the driver is drowsy. So, it can be said that the paper contains the architecture, methodology, and evaluation of the system. The result of the evaluation suggested that the system could correctly sense drowsiness with a high degree most of the times. However, the system's failures and improvements for the future are also discussed in the paper. In this paper **[18]** a driver drowsiness detection system based on a deep learning has been implemented but foremost relies on a Deep Convolutional Neural Network (CNN). The study addresses the increasing occurrence of road accident due to driver fatigue and suggests a model to detect driver drowsiness based on the driver's eye state. To detect the face, it uses Viola-Jones algorithm and extracts the eye region and then it passes it through a CNN with 4 convolutional layers to provide feature extraction. The SoftMax classifier classifies the eye images as drowsy or non-drowsy. On a dataset of 2,850 images, the model was trained with an 96.42% accuracy. The system was also tested in real time scenarios, where its analysed video frames and alerted the driver if drowsiness was detected. This paper points out the advantages of stacked Deep CNN over traditional methods. Possible future improvements involved applying transfer learning to improve the model performance across different kinds of conditions. Paper **[19]** has provided an RT real-time, non-invasive driver drowsiness detection using visual based features. The system records front-facing videos from the car’s dashboard mount, and identifies facial landmarks to estimate EAR, MAR, and head pose. These features are fed into three classifiers: Random Forest, Sequential Neural Network and Support Vector Machine. The result obtained from the insignificantly smaller National Tsing Hua University Driver Drowsiness Detection Dataset was an equally impressive 99% for the RF classifier. The system vibrates and sounds an alarm to inform the driver when the system discovers that the driver is sleepy. It is expected to be flexible for various vehicles such as cars and buses, among others. Further enhancements for future releases: creation of a mobile version of the extension for greater convenience, adjustments to how the cameras work with lighting. The work in **[20]** on detecting drowsiness of a driver has attracted much attention and interest because of the impacts on safe driving. The new eye blinking patterns have raised the ladder of consciousness level checking, on one hand, frequent and long blinks signify lethargy. Many methods namely computer vision, machine learning and physiological signals have been used for the purpose of drowsiness detection. For example, it has been proposed about eye-blink and yawning as two features and their comparison indicated that the use of these indicators increases detection specificity. Real-life applications have involved analysing frequency of eye-blinking in real-time with improved precision by the aid of CNNs. Previous works have used support vector machines (SVM) for reliable classification, focusing on the adequacy of the feature extraction. Such developments include real time tracking of head pose and rotation, and eye states and yawning using facial landmark detection and EAR calculation. Altogether, these novelties demonstrate the applicability of the deep learning and computer vision in designing the reliable drowsiness detection and, therefore, the goal of minimizing the number of crashes associated with tired driving.

The paper discussed different researches on AI Driven driver drowsiness and stress detection, with emphasis on the method of automatically selecting music for increasing driver attention and comfort. Nevertheless, there are still quite a few questions that have to be answered further: Firstly, most of the existing research performs well in detecting drowsiness and stress, but fewer of them focus on combining multiple inputs in order to enhance the distinguishing predictive accuracy for different driving situations. Secondly, it emerges that prior studies do not pay much attention to the main issues such as long-term consequences of chronic stress exposure while driving and its further influence on driver’s health. Lastly, there is a huge need to improve the user experience through various evaluation indicators that incorporate the true positive and the acceptance of automated actions.

The goal is to create an entire AI enabled tool to recognize drowsiness and stress in real time and provide personalized music interventions that will better engage the driver. That essentially means making generalized AI models that run well at all vehicle types and all driving scenarios, but also providing better accuracy by adding in more complex factors, such as environmental conditions and personal driver profiles. The objective is to offer a comfortable driver with safer surroundings reducing road accidents and enhancing more sustainable driving.

3. Methodology

To do that, we fully review existing research on driver monitoring technologies to develop the "AI-based Drowsiness and Stress Detection with Automatic Music Recommendation" system. Specifically, in detecting both stress and drowsiness, we focused specifically on physiological and behavioural indicators that can be observed, i.e., facial expressions, heart rate and skin temperature. This research demonstrated this is possible, and we developed a system that can identify these states in real time so drivers can be warned and provide personalized music recommendations to help alleviate stress while driving.

The core physiological and behavioural indicators we utilized in this system include:

- Accelerometer (ACC): Its application is for the tracking of any significant movement or vibration patterns.
- Blood Volume Pulse (BVP): Analyse variations in blood flow throughout the body to measure heart rate.
- Electrocardiogram (ECG): Its records heart's rhythm and electrical activity and displays the user's stress level.
- Electrodermal Activity (EDA): It monitors changes in the skin's electrical properties, which change depending on emotional states such as nerves.
- Body Temperature (TEMP): Body temperature fluctuations — sign of stress, or other physiological response — are provided.

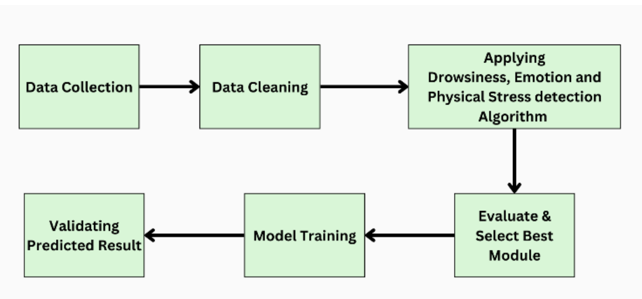

Figure 1: Level 0 System Model

Figure 1 provides the high-level view of the Level 0 System Model that depicts the flow of processes from data collection to the validation of the mentioned results above. The system starts by data gathering, data cleansing and data preparation stage. After this, we perform a regression algorithm to choose the best model, train the model and then test the results of the predicted model.

For drowsiness detection, we used labelled images of many models and retrained a pre-trained YOLOv10 model emphasizing blinking of eyes and yawning. For stress detection, we utilized different methods based on attribute types:

- Physical Attributes (e.g., heart rate, skin temperature): We used the LightGBM model because of its ability to fit in structured data sets and performance when numerous physiological variables are being used as input.
- Emotional Attributes (e.g., facial expressions): For the real-time analysis of facial data for emotional state assessment, we fine-tuned a conventional Convolutional Neural Network (CNN).

In case the drowsiness is sensed, the specific signal is designed to make a sound to wake up the driver. If stress is detected, it suggests calming music and includes Spotify and YouTube APIs to offer authors of the program several playlists aimed at reducing stress and increasing concentration levels among drivers.

4. Proposed System

The system that is under development will have potential to detect drowsiness and stress state in drivers with the help of physical and behavioural parameters including heart rate, skin temperature and facial expressions analysis. The system classifies the driver's state into one of three categories: drowsy, neutral, or stressed. The detection process comprises of the application of get Parent value by using enhanced machine learning methodology; YOLOv10 model used in the real-time drowsiness detection. This model is trained from a labelled data set consisting of images classified as awake or drowsy. Using OpenCV, the system sets the video capturing from the vehicular camera and for every frame, it passes it through the YOLOv10 model to detect either the driver is awake or drowsy. The outputs produced are in a video file format where the driver state is shown at each time step (output.mp4).

To predict stress, we employed LightGBM machine learning algorithm based on the WESAD dataset **[21]**. This dataset is packed with the complete physiological data that help the model to distinguish between stressed, amused or a state of neutrality. Combined with other inputs like heart rates and skin temperatures, the model is then able to learn stress inputs, thus being able to compute stress from new data and forecast the driver's mood. It enables the system to decide whether the driver is stressed or not.

For stress detection based on emotional attributes, we applied the Custom CNN model to be trained on the FER-2013 dataset **[22]** obtained from the Wolfram Data Repository (2018). This model is supposed to detect emotional stress based on facial expressions and emotion pointing to the driver in real time if, for instance, a video or an image is taken.

To ensure that the intervention is as individual as possible, the system offers a music recommendation component with Streamlit web app connected to Spotify, along with YouTube API. Depending on the driver's state, as well as stress or drowsiness, the system set in the car advises the driver to turn on music that is calming or energizing, respectively. As a user, they can either type in a specific song's name, or search through pre-defined stress-relief or energizing keywords. When the visitor presses the "Show Recommendations" button, the program looks for the corresponding songs in Spotify, mixes them up, and chooses ten best tracks and their links. All these tracks, URLs of those in YouTube, and album covers are shown in this app. The driver can click on the "Play Song" link which will play the song on You Tube to help the driver either calm down or listen to something that will keep him/her awake while driving.

This combination of real-time drowsiness and stress detection, along with personalized music recommendations, is aimed at enhancing both driver safety and comfort. By addressing critical factors like comprehensive solution to improve the overall driving experience and reduce the risk of accidents.

Table 1: Dataset table

Emotion	Number of Samples (%)
Angry	4953 (13.8)
Disgust	547 (1.5)
Fear	5121 (14.3)
Happy	8989 (25.0)
Sad	6077 (16.9)
Surprise	4002 (11.1)
Neutral	6198 (17.3)
Total	35,887 (100)

For the training of the physical model, we used a dataset with shapes: input features (1178, 12) and target (1178,). The dataset was split into training and test sets with the following splits: training set (1060, 12) and test set (118, 12). For the emotion model, we used a total of 35,887 samples, divided into a training set of 28,709 samples and a test set of 7,178 samples. The table 1 shows the number of samples and the percentage used for each.

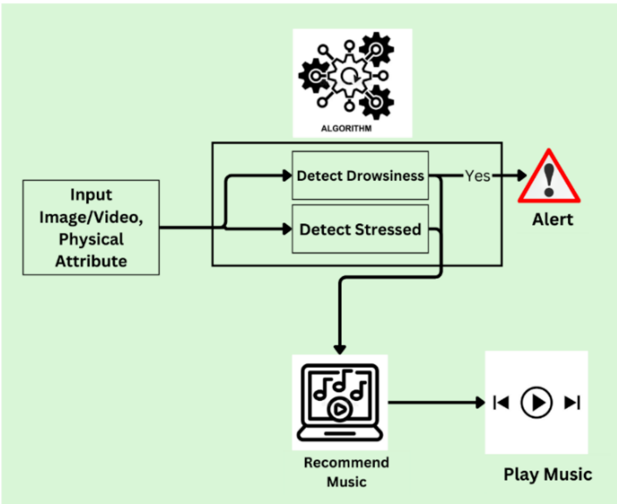

Figure 2: System Architecture

In figure 2, we illustrate the system architecture. The first step is to determine whether the driver is Drowsy or Stressed. If drowsy or stress is detected, the recommendation system is automatically initiated, which starts suggesting and playing songs based on the driver's keywords.

5. Result

This study introduces an AI Driven Drowsiness and Stress Detection System that employs two distinct models to assess a driver's condition in real-time. Drowsiness is detected using a YOLOv10-based deep learning model, while stress is identified using machine learning algorithms alongside facial emotion recognition techniques. Both systems work in unison to enhance driver safety and comfort by providing personalized interventions through music recommendations, depending on the detected condition.

- **Drowsiness Detection**

The drowsiness detection model is powered by a YOLOv10 deep learning architecture, trained specifically to recognize two states: awake and drowsy. The output was compiled into an output.mp4 video file, visually demonstrating the model's ability to detect whether the driver is drowsy or awake. When drowsiness is detected, the system triggers an intervention in the form of stimulating music recommendations to alert the driver.

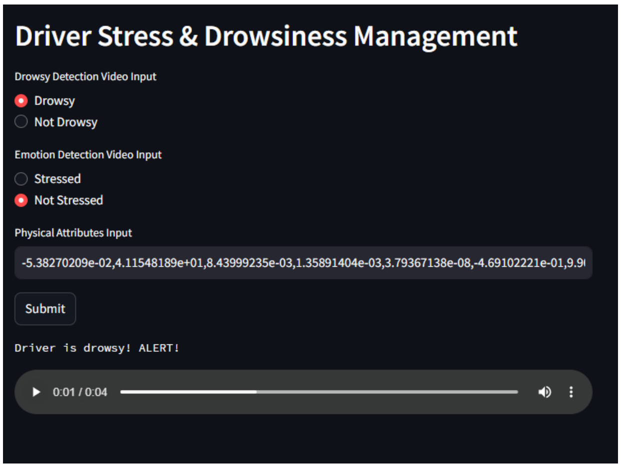

Figure 3: Drowsiness Output

As illustrated in figure 3, the model successfully identifies a drowsy state, prompting the system to take immediate action by providing recommendations for alertness-enhancing music to help keep the driver awake and attentive.

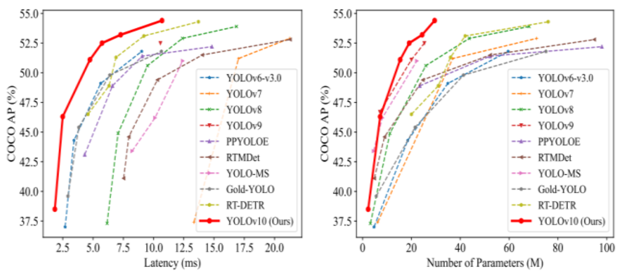

Figure 4: Performance comparison of YOLO Models

In figure 4 it is comparisons with others in terms of latency-accuracy (left) and size-accuracy (right) trade-offs. We measure the end-to-end latency using the official pre-trained models.

The YOLOv10-based drowsiness detection model demonstrated high efficiency and accuracy in real-time video inputs, accurately distinguishing between drowsy and awake states. This enables the system to take immediate action when drowsiness is detected, helping to prevent accidents due to driver fatigue.

- **Stress Detection**

In addition to drowsiness detection, the system assesses the driver's stress levels based on their physical attributes (heart rate variability, skin temperature) and facial expressions. The stress detection component uses machine learning models such as Random Forest, XGBoost, LightGBM, SVM, and KNN, which were previously trained on a dataset containing physical and emotional indicators of stress.

Table 2: Physical Attributes Model

Sr. No.	Model	Accuracy (%)
1.	Random Forest	92.37
2.	XGBoost	94.06
3.	LightGBM	96.61
4.	SVM	76.20
5.	KNN	71.18

The Table 2 provides information about the accuracy of different machine learning models used in the Smart Stress-Free Drive system for detecting driver stress levels. The accuracy percentages indicate how well each model can correctly classify a driver's emotional state into one of three categories: amused, neutral, or stressed. Random Forest: This model achieved an accuracy of 92.37%. It is a machine learning algorithm that uses a large dataset to make predictions about a person's emotional state based on their physical attributes like heart rate, skin temperature, and facial expressions. XGBoost: This model achieved an accuracy of 94.06%. XGBoost is another machine learning algorithm used in the system to predict driver emotional states. It performed slightly better than the Random Forest model. LightGBM: The LightGBM model achieved the highest accuracy of 96.61%. It is another machine learning algorithm used in the system, and it performed the best among all the models, indicating that it is very effective in classifying driver stress levels. SVM (Support Vector Machine): The SVM model achieved an accuracy of 76.20%. While it has a lower accuracy compared to the machine learning models, it is still useful for identifying driver stress levels based on the provided data. KNN (K-Nearest Neighbours): The KNN model achieved the lowest accuracy of 71.18%. It is a different machine learning approach, and it performed less accurately compared to the other models.

Table 3: Emotional Model:

Sr. No.	Model	Architecture	Accuracy (%)
1.	Model 1	MobileNet Feature Extractor with Custom Classification	49.129
2.	Model 2	Custom CNN for Emotion Recognition	62.000

The deep learning model is a Convolutional Neural Network (CNN) designed for facial emotion recognition. It comprises multiple layers, including Conv2D layers to extract image features, MaxPooling2D layers for down sampling, Dropout layers for regularization, and Dense layers for classification. The model takes grayscale images of size 48x48 as input and outputs probabilities for seven different emotion classes (e.g., happy, sad, angry) using a SoftMax activation in the final layer. Dropout layers help prevent overfitting, and ReLU activation functions are applied in most layers to introduce non-linearity. This architecture is structured to capture intricate facial features and their spatial relationships, making it suitable for the emotion recognition task.

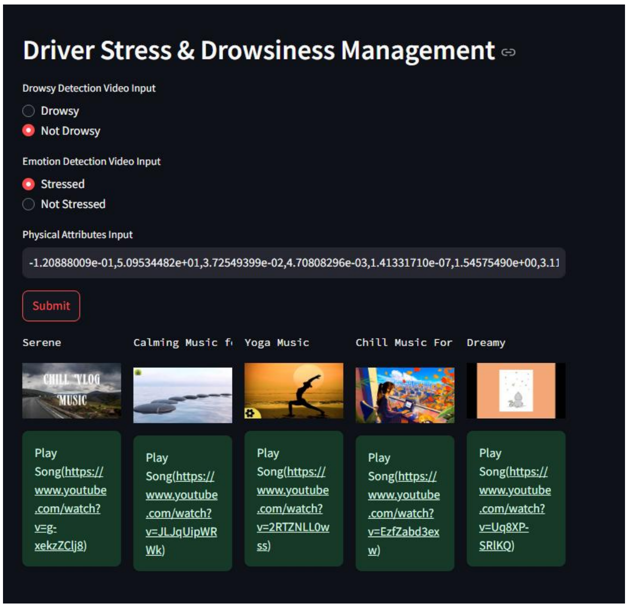

Figure 5: Stress Output

As illustrated in figure 5, the model successfully identifies a stressed state, prompting the system to respond by suggesting calming music to help reduce the driver's stress levels and improve their focus on the road.

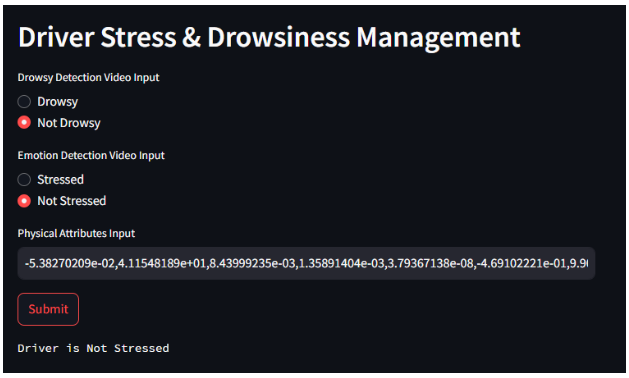

Figure 6: Not Drowsy & Not Stressed Output

Conversely, as shown in figure 6, the model correctly identifies that the driver is neither drowsy nor stressed, indicating that no intervention is required, and the driver remains in an optimal state for driving.

The integrated system effectively detects both drowsiness and stress, ensuring a comprehensive assessment of the driver's condition. When a driver is detected as drowsy, the YOLOv10 model triggers an alert, and energetic music is recommended to improve the driver's alertness. In cases of stress, detected by both the machine learning and facial emotion recognition models, soothing music is played to calm the driver.

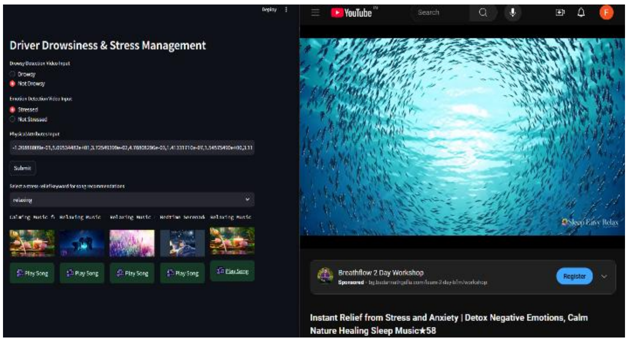

Figure 7: Music Recommendation

As shown in figure 7, the integrated system correctly detects both drowsiness and stress state of driver and recommend the appropriate music to calm the driver.

6. Conclusion

The "AI Driven Drowsiness and Stress Detection with Automatic Music Recommendation" system is designed to enhance driving safety and comfort by monitoring both the driver's drowsiness and stress levels in real-time. Using advanced deep learning models like YOLOv10 for drowsiness detection and other machine learning models for stress detection, the system accurately identifies when the driver is fatigued or stressed.

Future improvements could include integrating additional contextual information such as road conditions, time of day, and driver schedules to further personalize the recommendations. Furthermore, expanding beyond music, the system could offer relaxing videos or motivational content to assist drivers in maintaining both alertness and emotional stability. Overall, this AI-powered system holds great potential for reducing driver fatigue and stress, leading to safer and more enjoyable journeys.

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