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CHAUFFEUR EXHAUSTION TRACKING SYSTEM USING MACHINE LEARNING

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Abstract - These days, a growing number of professions demand sustained focus. Chauffeurs need to pay attentive attention to the road so they can respond quickly to unexpected incidents. The primary factor in numerous traffic accidents is frequently chauffeur weariness. Consequently, it is necessary to create a system that can identify drowsiness in a chauffeur and alert them to it, which might greatly reduce the frequency of accidents caused by weariness. The development of such systems, however, has numerous challenges when it comes to accurately and promptly identifying a chauffeur's signs of sleepiness. The employment of a vision-based technique is one of the technical options for implementing chauffeur drowsiness tracking systems. This project recognizes the chauffeur's tiredness and sends a warning sound to remind him to stay awake. Here, we estimate the chauffeur's vision system in order to determine his level of tiredness.

Index Term – **Chauffeur Drowsiness Tracking, Eye Tracking System, Exhaustion, Convolutional Neural Network**

I. INTRODUCTION

The necessity for movement has become absolutely necessary for every person in the modern world. Almost 70% of respondents choose private autos over public transportation. Chauffeurs frequently have to operate motor vehicles through the night without any rest. Auto accidents involving fatigued chauffeurs have significantly increased in recent years. Automobile accidents were one of the top 10 causes of mortality for people in 2015, according to a World Health Organization (WHO) report [1]. As the central component of the road traffic system, the chauffeur is, as is well known, the most important element influencing road traffic safety. According to research conducted on the 300-km Agra-Lucknow Expressway in India by the Central Road Research Institute (CRRI), fatigued chauffeurs who fall asleep behind the wheel cause 40% of traffic accidents. This is especially relevant to tired chauffeurs who fall asleep behind the wheel on our roadways between midnight and five in the morning. As information technology has advanced, drowsy driving tracking systems have emerged as an alternative method of resolving the issue.

Research on the intelligent tracking of drowsy driving therefore has significant realistic implications.

By recording the chauffeur's eyes, we've included a drowsiness tracking system to help reduce accidents caused by driving fatigue. The frequency and timing of eye blinking serve as important parameters. As a motorist begins to feel sleepy, an alert system is suggested to let them know. During this idea, a novel strategy to driving safety and accident avoidance based on Chauffeur Drowsy Tracking System is projected. Automobile fatigue-related crashes have significantly increased in recent years. in order to prevent car accidents brought on by chauffeur drowsiness tracking systems. By taking a picture of the chauffeur's eyes, we've added a drowsiness tracking system. The frequency and timing of eye blinking serve as important parameters. As a motorist begins to feel sleepy, an alert system is suggested to let them know. The current methods use support vector machines (SVMs) to categorize the different parts of the input video. The target area of the person is not accurate when the region of interest components in the video are cropped. The system occasionally notices these regions and reports them as incorrect. We must design boundary boxes specifically for the eyes in order to precisely perceive the status of the eyes, which will subsequently be detected and recognized by a classification algorithm. As a result, the SVM algorithm will not produce correct results.

Eye tracking and monitoring algorithms and techniques come in a variety of forms. The majority of them had something to do with the chauffeur's eye characteristics in a video image. This project's original intent was to locate the eyes on a face using the retinal reflection, and to determine whether the eyes are closed by observing whether the reflection is present or not. Calculating the eye closing period may be facilitated by using this algorithm to successive video frames. Chauffeurs who are drowsy have longer periods between closing their eyes than usual. Even though it takes a tiny bit longer, a devastating collision could happen. So, the moment we notice a closed eye, we will alert the chauffeur. We employ the CONVOLUTIONAL NEURAL NETWORK (CNN) Algorithm to identify sleepiness. The three layers of a convolutional neural network are the input layer, the hidden layer, and the output layer. Any middle layers in a feedforward neural network are referred to as hidden layers since the activation function and final convolution hide their inputs and outputs. Convolutional layers are found in a convolutional neural network's hidden layers. This often has a layer that does multiplication or another dot product, and its activation function is frequently ReLU. Following this are more convolution layers like normalizing, pooling, and fully linked layers. A collection of pictures of chauffeurs with closed eyes is used to feed this algorithm. Every iteration of the CNN's training yields an accuracy using the same dataset for n iterations. After comparing the input image derived from the camera's video stream, CNN stores the most accurate model it can find. The CNN trained model notifies the chauffeur by making an alert sound, which continues to be created until the person opens his eyes. Even after the chauffeur opens his eyes, the alert sound continues to be produced for a while until our target frequency is reached.

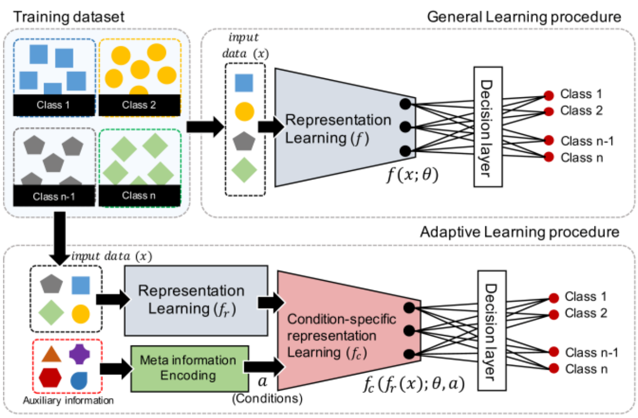

Fig. 1. Block diagram depicting different steps of Convolution Neural Network training on a Chauffeur Drowsiness images.

II. LITERATURE SURVEY

Chauffeur exhaustion assessment using a spatiotemporal convolutional neural network based on EEG

The analysis of chauffeur weariness is crucial for traffic safety, and it would be made more difficult by several complex aspects. In this study, we create a unique EEG-based spatial-temporal convolutional neural network (ESTCNN) to identify chauffeur exhaustion based on the spatial-temporal structure of multilayer electroencephalogram (EEG) inputs. In order to extract temporal relationships from EEG data, we first present the core block. In order to combine spatial data and achieve classification, we then use thick layers. The created network outperformed the traditional two-step machine learning techniques by immediately learning meaningful characteristics from EEG data. We also conduct driving fatigue tests to gather EEG data from eight people in alert and fatigued phases. We assess the efficacy of ESTCNN with eight other approaches using 2800 datasets under within-subject splitting. The findings show that ESTCNN outperforms these comparison approaches in terms of classification accuracy, scoring 97.37%. Additional implementations in the brain-computer interface online systems are made possible by the spatial configuration of this framework, which has benefits in computing efficiency and reference time.

The classification of videos using two-stream shared instruction with spatial-temporal awareness

Video categorization is crucial and has many uses, including intelligent surveillance and video search. Frames and image filtering, which may be used to describe static and dynamic information, respectively, are inherently present in video. Deep networks are frequently used by academics nowadays to record static and motion data independently, however this approach has two major drawbacks. First, despite the fact that they should be simultaneously modelled as the spatial and temporal evolutions of video to learn discriminative video characteristics, the link between temporal and spatial attention is overlooked. Second, despite the fact that static and movement data have high synergies and should be jointly learnt to complement one another, this relationship is ignored. This work suggests the two-stream collaborative learning with spatial-temporal attention (TCLSTA) strategy, which consists of two models, to overcome the aforementioned two drawbacks. (1) Model of spatial-temporal attention The prominent areas in a frame are highlighted by spatial level attention, and the discriminative frames in a movie are taken advantage of by temporal level attention. Together, they learn the differentiating static and motion cues to improve classification performance. (2) Static-motion collaborative model: It takes use of the high compatibility between static and motion data to enhance video classification by achieving mutual mentoring between static and motion data as well as adaptively learning the fusion values of static and motion streams. Studies on four frequently used datasets demonstrate that our TCLSTA methodology outperforms more than ten cutting-edge techniques.

A persistent network of spatial and temporal attention for recognizing actions in recordings

Recurrent neural networks (RNNs) have been increasingly popular in recent years for action identification in videos. Recordings, on the other hand, are highly complex and rich in interpersonal dynamics with various flow scales, which makes it challenging for typical RNNs to capture complicated action information. We provide a spatial-temporal attention mechanism to adaptively select relevant elements from the overall video context for each timestep prediction of RNN in this paper's proposal of a novel recurrent spatial-temporal attention network (RSTAN) to meet this difficulty. We especially contribute in three ways from the following categories. First, we add a brand-new temporal and spatial attention module to the traditional long short-term memory (LSTM). Our module can automatically generate a concise, highly applicable spatial-temporal action representation for the current time step from all captured video frames. Second, we develop an attention-driven appearance-motion fusion technique to combine motion and appearance LSTMs into a single framework, enabling the end-to-end training of Long short - term memory with underlying visual attention configurations in two streams. Third, we provide actor-attention regularization for RSTAN, which directs our learning algorithm to pay attention to key activity zones around players. Using the benchmark UCF101, HMDB51, and JHMDB data sets, we assess the proposed RSTAN. The experimental findings demonstrate that our RSTAN reaches the condition on JHMDB and surpasses other recent RNN-based techniques on UCF101 and HMDB51.

Chauffeur exhaustion tracking using a representation learning framework for condition-adaption

Relying on a 3-dimensional convolutional neural network (CNN), we provide a circumstance model learning framework for driving fatigue tracking. Four models make up the suggested framework: sleepiness tracking, feature fusion, scene condition interpretation, and learning of spatiotemporal representations. Learning spatial-temporal representations allows for the extraction of features that may concurrently characterize movements and appearances in videos. Scene condition comprehension categorizes scene circumstances relating to several aspects of chauffeurs and driving scenarios, such as eyeglass use status, lighting conditions while driving, and head, eye, and mouth motion. Using two features collected from the aforementioned models, feature fusion creates a condition adaptable representation. The condition-adaptive representation is used by the sleepiness tracking model to identify chauffeur drowsiness. The sleepiness tracking approach may deliver more accurate results for the various driving scenarios thanks to the condition-adaptive representation learning framework's ability to extract more discriminative features concentrating on each scene condition than the generic representation. With the help of the NTHU sleepy chauffeur tracking video dataset, the suggested framework is assessed. The experimental findings demonstrate that our framework outperforms the current visual analysis-based sleepiness tracking approaches.

Detecting chauffeur exhaustion based on heart rate fluctuation and evaluating it with EEG

A crucial piece of technology that can stop deadly automobile accidents brought on by fatigued driving is chauffeur drowsiness tracking. The current study suggests a heart rate variability (HRV)-based chauffeur drowsiness tracking system and verifies it by comparing it to an EEG-based sleep grading technique. The autonomic nervous system, which is characterized as an RR interval (RRI) variation on an ECG trace, is impacted by changes in sleep quality. A well-known technique for anomaly identification called multivariate statistical process control is used to monitor eight HRV variables for variations in HRV. Results: A driving simulator experiment was used to gauge how well the suggested algorithm performed. In this study, 34 individuals drove while their RRI information was gathered, and a sleep expert used the EEG data to pinpoint the start of each participant's sleep. The experimental data were validated using EEG data, and the results revealed that 12 out of 13 pre-N1 episodes had tiredness present before the start of sleep, with a false positive rate of 1.7 times per hour. Conclusion: The current work also confirms the applicability of the HRV-based anomaly tracking system, which was initially suggested for seizure prediction. Importance: The suggested technique may help to reduce crashes brought on by fatigued driving.

III. IMPLEMENTATION

Video Input:

The input video is the live footage that was captured by the camera. This camera records the target's face and eyes while they are operating the vehicle. The next process will be informed by this video.

Frame Separation:

Frame processing is the first phase in the background subtraction technique. Its goal is to modify the video frames by eliminating noise and undesired objects in order to increase the amount of information that can be extracted from each frame. Preprocessing a picture might involve a collection of straightforward image processing operations that convert the unformatted raw input video data into a format. Next stages might handle processing the frames.

Preprocessing of the video is required to improve the recognition of moving objects. For instance, snow that seems to be moving leaves on a tree might be eliminated by morphological processing of the frames after the moving item has been identified. To process the video stream, pictures must be created from it. In order to transform the video feed into frames per second. They are sent to the pre-processing as input.

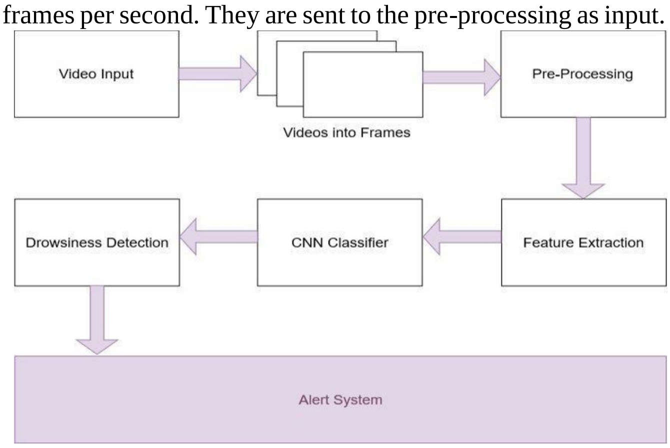

Fig 2. Work flow diagram

Image pre-processing:

A signaled picture is frequently pre-processed to eliminate noise. A crucial pre-processing step to improve the outcomes of subsequent processing is noise reduction. The median filter's primary function is to restore each item with the median of its nearby entries by processing the signal entry by entry.

The following steps are significantly involved in image processing: i. Using image acquisition tools to import the image; ii. Analyzing and altering the image; and iii. Output, which might be a transformed image or a report based on the analysis of that image.

Feature Extraction:

A method of dimensionality reduction called feature extraction effectively depicts the visually appealing elements of a picture as a compact feature vector. When an algorithm's input file is too huge to process and is thought to include redundant information, it may be decreased in size. The process of selecting a portion of the first features is known as feature selection. In order to complete the desired job using this condensed representation rather of the whole starting data, the selected features are anticipated to include the pertinent data from the input file. This method is helpful when huge picture files need a reduced feature representation for applications like image matching and retrieval. The set of sleepy photos is used to identify the drowsiness traits. The location of the eye and the length of time it is closed are examples of these characteristics. The characteristics are taken from the several occurrences of passengers getting sleepy in the cars.

CNN Algorithm:

Artificial neural networks are used to classify numerous types of data, including text, audio, and images. Making a decision on a suitable design and learning algorithm is crucial to achieve the best outcomes while utilizing the neural network. The size of the neural network is expanded or shrunk based on the findings from earlier research publications until a satisfactory output is attained. In this study, we used Python to test several neural network sizes and discovered that this was the most effective one. Various types of neural networks are employed for different tasks. For example, we use recurrent neural networks—more specifically, an LSTM—to predict the order of words, while we use convolutional neural networks to classify images. The components of a convolutional neural network include an input layer, hidden layers, and an output layer.

Any intermediary layers in a feed-forward neural network are referred to as hidden layers since the activation function and final convolution hide their inputs and outputs. The hidden layers of a convolutional neural network contain convolutional layers. This often contains a layer that performs multiplication or another dot product, and ReLU is frequently used as that layer's activation function. Further convolution layers, including pooling layers, fully linked layers, and normalizing layers, come after this. The CNN algorithm receives the feature-extracted dataset and trains on it for n rounds. Each training cycle yields an accuracy. The CNN algorithm selects the most accurate model from the training set. The CNN uses this concept to produce a significant amount of output.

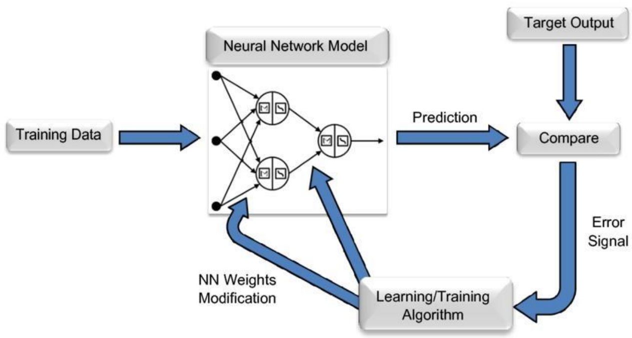

Fig 3. Working of CNN

Chauffeur Tracking:

The purpose of drowsiness tracking technology is to use mathematical algorithms to determine a person's level of tiredness. It belongs to the field of computer vision. The physical state of being known as fatigue causes people to close their eyes. Chauffeur Drowsiness Tracking is one of the areas of interest at the moment. Those who feel sleepy while operating a car will receive a warning. Cameras and computer vision algorithms have been used in a variety of ways to interpret eye closure positions. By warning the person at the right time, drowsiness tracking can be considered as a method for computers to save thousands of lives. As our sleepiness dataset has previously been used to train the CNN algorithm. The pictures from the vehicle's video stream are used to feed the CNN Algorithm. The best precise trained model that CNN has is used to compare these photos. When both conditions are met, the device identifies the person's sleepiness. It also checks how long the person's eye is closed and, if it exceeds a threshold value, sends the information to the audio system.

Alert System:

Text messages are converted into auditory signals by an alert system. The production of audio warnings involves several technologies. Among those, PyAudio was the most appropriate and accurate element. The cross-platform audio I/O package PortAudio has Python bindings available due to PyAudio. The textual signal produced during the phase of sleepiness tracking is provided to PyAudio as input. This text signal is transformed by PyAudio into an alert that cautions people until they open their eyes and remain open for a certain period of time..

IV.RESULT AND ANALYSIS

Our methodology guarantees a fully automated solution to identify tiredness in a chauffeur. The effectiveness of the suggested method was precise and capable of identifying people's tiredness under various lighting conditions. We only take into account eye tracking since we are interested in detecting sleepiness. It is used to identify face eyes. The person's face is framed by a box that draws the viewer's attention to it. When the estimated eye closure time span exceeds the predetermined threshold, we call it. It begins to alarm very subtly. If the person's eye closure posture doesn't change, the alert volume steadily rises until the person opens their eyes. The alarm system gradually lowers in loudness as soon as the person opens their eyes, and after a certain number of seconds it switches off.

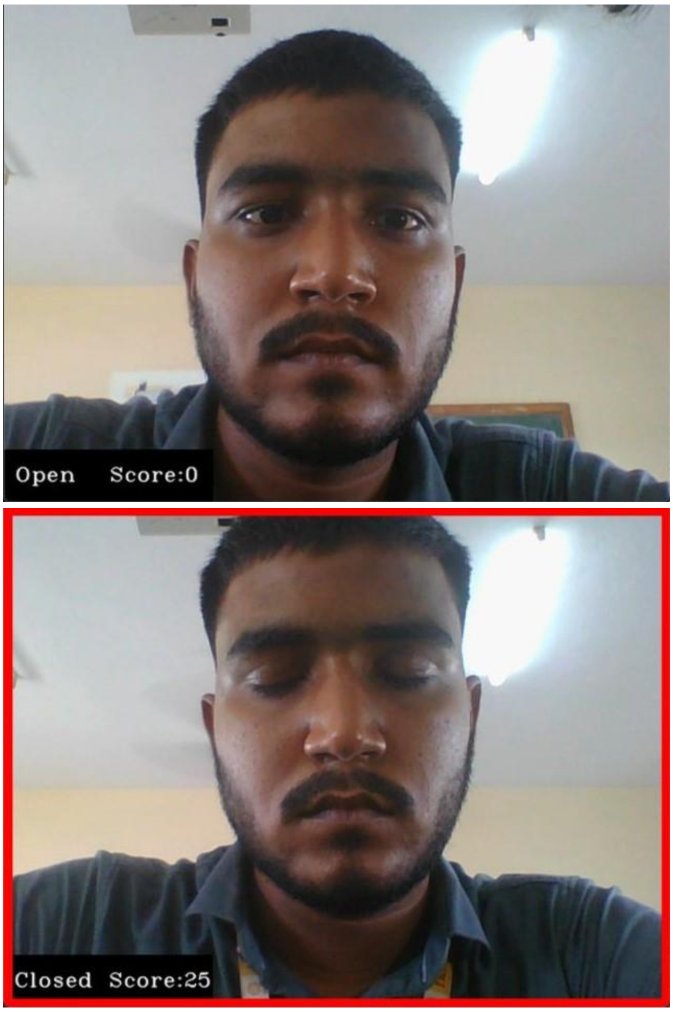

Fig.4 Results of proposed system

V.CONCLUSION

The identification of sleepiness from the captured live video is presented in this paper. By contrasting the facial expressions recorded on camera with the standard dataset provided from Kaggle, the chauffeur's tiredness is identified. Drowsiness may be quickly identified by the designed chauffeur anomaly monitoring system. The Drowsiness Tracking System, which was created based on the chauffeur's eye closure, is able to distinguish between regular eye blinking and tiredness and can identify drowsiness while driving. The suggested technique can avoid accidents brought on by chauffeurs who are sleepy. If the camera produces superior results, the system still functions effectively even when the chauffeur is wearing eyeglasses and in low light. The monitoring device can determine whether the eyes are open or asleep. An alarm signal is given when the eyes are closed for an extended period of time. So, chauffeurs may significantly reduce their risk of accidents by applying this idea. Convolutional neural networks are used for this. This project is an effort to aid chauffeurs who regularly travel at night. With the use of this initiative, we can quickly identify sleepiness and notify the chauffeur of any urgent situations. The results of the studies indicate that the recommended method has produced results that are more accurate than the previously used approach. Data scientists have already created the data set, and their accuracy rate is 92.4%. We added CNN to the project to increase its accuracy. In comparison to the current model, the outcome is more efficient and performs better.

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