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DRIVER GESTURE MONITORING AND NOTIFYING SYSTEM FOR ANALYZING THE VEHICULAR SAFETY

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Abstract:

Through the Internet of Vehicles, here develops a framework for Warning and Monitoring System for analyzing the vehicular safety is to identify potentially unsafe driving. The developed DGMN framework uses wearable technology and onboard image sensors to track driver head motion and determine the degree of vehicle departure, respectively. This system uses the Longest Common Subsequence (LCS) algorithm to determine the similarity between the sensed motion feature vector (measuring in real time) and the target motion feature vector (capturing in advance). Hand gestures are investigated as an alternate or supplemental input modality for mobile devices in this paper. It is presented a novel gesture recognition system based on the usage of an acceleration sensor, which is currently found in an increasing number of consumer electronic gadgets. Accelerometer sensor data may be used to detect hand motions and categories them into previously taught gestures. To increase the accuracy of closest neighbor classification, the suggested approach employs Mahalanobis distance metric learning. To validate the feasibility and superiority of DGMN, a prototype comprising of an Android-based sensing unit and an Arduino-based wearable device is constructed. DGMN beats existing approaches in terms of detection accuracy and false alarm rates for unsafe driving behaviors, according to experimental data.

Keywords — Internet of Vehicles, Gesture recognition, Image recognition, Intelligent transportation system, Vehicle to vehicle communication.

I. INTRODUCTION

Gestures are important in many facets of human existence. A range of spontaneous gestures, such as finger, hand, head, and other physical moves, are an important element of ordinary human interactions. Gesturing enables people to express specific messages with the purpose of delivering relevant information, frequently in conjunction with body language in addition to words while speaking. Gestures may thus be thought of as a natural communication channel with different elements that can be used in human-computer interaction.

Traffic accidents are a major global public concern. The increasing number of individuals injured or killed in car accidents demonstrates the world's concern with road safety. Road traffic accidents are the third leading cause of death for those aged 30 to 44, and the second leading cause of death for people aged 5 to 29. Thanks to recent developments in mobile networking and embedding MEMS technology, the Internet of Vehicles (IoV), which can accomplish the advantages of both vehicular adhoc networks and wireless sensor networks, is now viable. IoV communications may be used to develop cutting-edge automotive applications like chain collision avoidance, dynamic traffic control, video-based urban positioning, cooperative lane placement, etc.

On-road vehicles frequently employ the Global Positioning System (GPS) for external localization. Lane deviation estimate is a useful technique for evaluating driver behaviour since dangerous driving while exhausted, inebriated, distracted, etc. commonly results in aberrant lane departure. The GPS position calculation does, however, contain

both global and local errors. Multipath effects, which are worsened in urban environments by towering structures, are the main cause of local errors. For instance, in a setting with several tall buildings, GPS position is unreliable enough to predict lane departure owing to faults of more than 10 metres.

With the spread of MEMS (Micro Electro Mechanical Systems) technology, consumer electronics today are increasingly incorporating a variety of precise sensors, such as accelerometers and gyroscopes that allow them to measure acceleration and orientation, respectively. Examples of these devices include mobile phones and game consoles. The inclusion of these sensors in these "smart" mobile devices, together with their mobility, robust computational capacity, data-sending and data-receiving capabilities, and their pervasive use in contemporary culture, has created new opportunities for the study of gesture-based interaction technology. Since most mobile operating systems primarily employ motion data to select between screen orientations, these new developing interaction modalities have not yet had a significant influence on how people engage with devices.

An accelerometer is a tiny sensor that can gauge the acceleration of either the device it is integrated into or itself. It is feasible to classify gestures into those that have already been established based on the acceleration profile that results from the device's movement. Numerous articles have examined this specific gesture detection method, and numerous input devices have been tested.

In this study, we develop an IoV-based system for driver behaviour monitoring and warning (DGMN) that integrates head wearables, onboard image sensors, and IoV communications. DGMN is the first framework for driver behaviour monitoring and warning that offers the following functions, according to our review of pertinent literature. Through an onboard image sensor, DGMN can continue to locate lane lines and calculate the power spectral density of lane deviation for a vehicle; through a head wearable device, DGMN can continue to monitor driving behaviours and gauge the level of driver anomaly; and through vehicle-to-infrastructure communications and Wi-Fi/4G, DGMN can instantly warn other vehicles and pedestrians of potentially hazardous driving.

We suggest a novel accelerometer-based gesture recognition system that uses closest neighbour classification and distance metric learning. In the developing field of distance metric learning, the underlying metric is modified in order to enhance classification and pattern recognition outcomes. Distance metric learning is a very new method that hasn't yet been used in this particular industry.

Our framework contributes in four key ways. In order to gauge the extent of lane departure of a vehicle, it is first possible to continually detect changes in the slope of its placed lane lines. Second, it is possible to continuously sense the feature vectors of a driver's head motion behaviours to assess the driver's level of abnormality. Third, to avoid potential collisions or accidents, the warning of identified risky driving may be quickly transmitted to surrounding cars and nearby pedestrians using IoV communications. Based on the driver's anomalous level measurement and the vehicle's projected lane departure. Finally, the IEEE 802.11p radio interfaces are used to create the prototype of our IoV communications system.

The rest of this paper is structured as follows. The related works which provide support and served as reference to this work is in Section 2. The proposed system architecture is described in Section 3. The implementation details are presented and discussed in Section 4. The result analysis is described in Section 5. The Section 6 deals with the conclusion of the system.

II. RELATED WORK

Reference [1] presents a non-intrusive prototype computer vision system for real-time monitoring driver's vigilance. It is based on a hardware system, for real time acquisition of driver's images using an active IR illuminator, and their software implementation for monitoring some visual behaviors that characterize a driver's level of vigilance. These are the eyelid movements and the pose face. The system has been tested with different sequences recorded on night and day driving conditions in a motorway and with different users.

Reference [2] examines hand gestures as an alternative or supplementary input modality for

mobile devices. A new gesture recognition system based on the use of acceleration sensor, that is nowadays being featured in a growing number of consumer electronic devices, is presented. Accelerometer sensor readings can be used for detection of hand movements and their classification into previously trained gestures.

Reference [3] presents a method for detecting the early signs of fatigue/drowsiness during driving. Analysing some biological and environmental variables, it is possible to detect the loss of alertness prior to the driver falling asleep. As a result of this analysis, the system will determine if the subject is able to drive. Heart rate variability (HRV), steering-wheel grip pressure, as well as temperature difference between the inside and outside of the vehicle, make possible to estimate in an indirect way the driver's fatigue level. A hardware system has been developed to acquire and process these variables, as well as an algorithm to detect beats and calculate the HRV taking into account the others aspects mentioned before.

Reference [4] present a lane detection and tracking approach designed to work in challenging environments where lane boundaries may be low-contrast and changeful with noise due to a number of factors such as wear, type, lighting and weather conditions, etc. In the method, a sophisticated cascade lane feature detector is applied to cope with challenging environments at the very beginning of the detection and a weighted graph is subsequently constructed by integrating intensity as well as geometry cues, reflecting the confidence of each pixel as a lane feature. In order to deal with complex road geometry, we employ Catmull-Rom splines to represent lane boundaries and the left and right lane boundaries are estimated separately in a tracking process using particle filter based on the weighted graph.

Reference [5] propose a robust real-time embedded platform to monitor the loss of attention of the driver during day and night driving conditions. The percentage of eye closure has been used to indicate the alertness level. In this approach, the face is detected using Haar-like features and is tracked using a Kalman filter. The eyes are detected using principal component analysis during daytime and using the block local-binary-pattern features during nighttime. Finally, the eye state is classified as open or closed using support vector machines. In-plane and off-plane rotations of the driver's face have been compensated using affine transformation and perspective transformation, respectively.

III. PROPOSED SYSTEM

Each vehicle in the DGMN system has an image sensor (such as a camera) in its front end, and each driver has a wearable device (such as headphones or a cap with acceleration sensors) on his or her head. The image sensor is used to find the current lane and assess a vehicle's degree of lane departure. The wearable gadget is used to gauge a driver's degree of anomaly and detect head movements.

Users are given a mobile device with a built-in three-dimensional accelerometer, such as a smartphone. The system is made up of a knowledge database that keeps track of various gesture sets and the actions that go with them, as well as a gesture recognizer algorithm that uses the tracking information gathered from the user to identify the gestures. The accelerometer sensor constantly detects and records any gestures made by the user. The noise from the acceleration data is then removed, and it is then sent to a feature extraction module, which converts it into a matching feature vector.

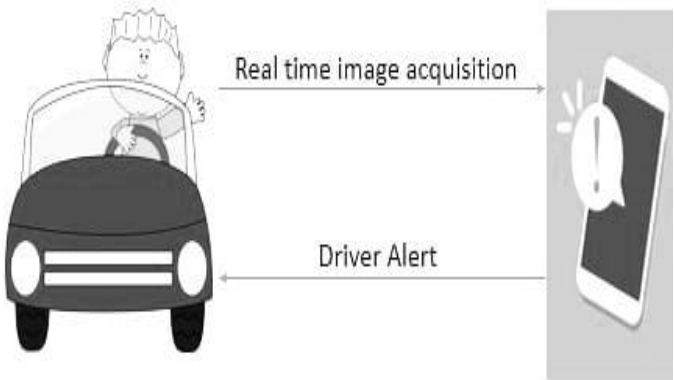

Fig 1: Image capturing & notifying

Giving the safety-dedicated channel the highest priority will decrease the chance of collision and the amount of time DGMN warning signals take to transmit (through the enhanced distributed channel

access introduced in the IEEE 802.11p standard). In order to communicate with pedestrians utilising cell phones, Wi-Fi/4G networks and vehicle-to-infrastructure links are also used. DGMN produces a high-frequency sound and high-degree vibration from a wearable device to warn the anomalous driver and convey alerts to surrounding pedestrians and other nearby cars when a vehicle's abnormal deviation and its driver both display high degrees of anomaly at the same time. The goal is to precisely identify the driver behaviours for risky driving notice by addressing the four research issues listed below:

1. Head Motion Recognition
2. Lane Deviation Measurement
3. Determining Harmful Driving Behaviors
4. Emergency Notification
5. Gesture Recognition

1. Head Motion Recognition

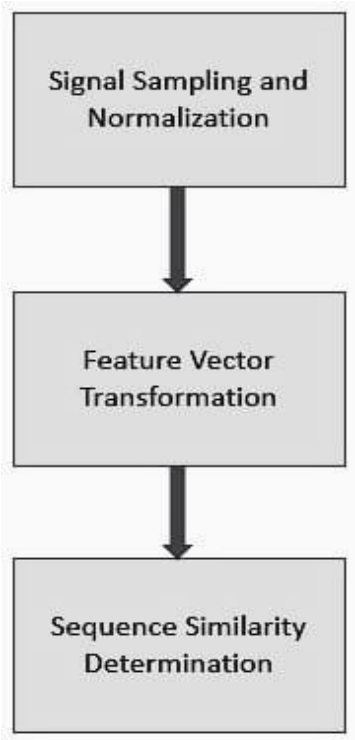

Fig 2: Flowchart of head motion recognition

LCS algorithm is used to determine anomaly level of the driver using HWD. Motion feature vectors included are: Sensed motion feature vector (measuring in real time), Target motion feature vector (capturing in advance). LCS algorithm determine the similarity between the both motion feature vectors.

		0	1	2	3	4	5	6	7	8	9
			C	B	A	B	C	A	B	C	C
0		0	0	0	0	0	0	0	0	0	0
1	A	0	↑0	↑0	↖1	←1	←1	←1	←1	←1	←1
2	B	0	↑0	↖1	↑1	↖2	←2	←2	↖2	←2	←2
3	C	0	↖1	↑1	↑1	↑2	↖3	←3	←3	↖3	↖3
4	A	0	↑1	↑1	↖2	↑2	↑3	↖4	←4	←4	←4
5	B	0	↑1	↖2	↑2	↖3	↑3	↑4	↖5	←5	←5
6	C	0	↖1	↑2	↑2	↑3	↖4	↑4	↑5	↖6	↖6
7	B	0	↑1	↖2	↑2	↖3	↑4	↑4	↖5	↑6	↑6
8	A	0	↑1	↑2	↖3	↑3	↑4	↖5	↑5	↑6	↑6

Fig 3: LCS metrics for S1 &S2

Maximum length of LCS matrix for sequences, S1= CBABCABCC & S2= ABCABCBA is 6
LCS(S1, S2) =ABCABC
Matching rate Rm of two motion feature vectors is:

$$R_m(S_M, S_T) = \sum_{i=1}^{n} \frac{|LCS(S_M, S_{T_i})|}{n}$$

DGMN uses the LCS algorithm to compare all possible numbers of feature values in S_T with S_M.

2. Lane Deviation Measurement

DGMN continuously detects and recognises the located lane utilising image processing methods through the onboard camera device (OCD). The OCD records the video frame with the lane markings on the road section. To create continuous lane lines from discrete lane markings, many recorded frames are overlaid. Canny edge detection is only carried out on the lower portion of the overlayed picture in order to lessen the processing cost of DGMN. The lower portion of the picture is next transformed into a binary, black-and-white image. The Hough line detection algorithm is then used to eliminate any identified edges on the binary picture that are not continuous lines.
Last but not least, a single lane line is created by combining close lane edges using linear regression.

In specifically, the slopes of the lane lines, where the left lane line slope is greater than zero and the right lane line slope is lower than zero in the located lane, may be used to determine the current located lane of the vehicle. Additionally, depending on the slope variation of the lane lines in the identified lane, the vehicle's degree of deviation may be calculated.

3. Determining Harmful Driving Behaviors

Each vehicle vi's state transition for detecting risky driving where the vehicle vi is initially in the Safe Mode state. Vehicle vi could be in one of four states:

- Safe Mode: If neither the driver's high level of abnormality nor the vehicle's excessive lane deviation are found, the driver of vehicle vi is operating the vehicle properly.
- Driver Anomaly: If the sensed motion feature vector measuring in real time is similar to the desired motion feature vector capturing in advance, the high anomaly level of the driver in vehicle vi is detected.
- Vehicle Deviation: If the amplitude sum of the power spectral density at each frequency for the lane line slope changes of vehicle vi is unusually high, this indicates a large lane deviation.
- Unsafe Mode: When the driver of vehicle vi exhibits both a high level of abnormality and a high degree of lane deviation, both are simultaneously identified, and warnings of dangerous driving are delivered to nearby vehicles and pedestrians.

4. Emergency Notification

Due to DGMN's detection of the driver's high degree of abnormality and the vehicle's irregular lane deviation, the vehicle vi enters the Dangerous Mode state, DGMN sends alerts to adjacent pedestrians and other nearby cars. To alert the driver in vehicle vi, DGMN also immediately emits a high-frequency sound and high-level vibration. In contrast, a vehicle that gets a DGMN warning message through vehicle-to-vehicle communications can be made aware of the risky driving behaviour in advance to prevent accidents. Similar to this, a pedestrian using a smartphone who gets a DGMN warning message via vehicle-to-infrastructure communications and Wi-Fi/4G networks can continue to warn to lessen the likelihood of accidents between the dangerously driving vehicle and this alerted pedestrian.

6. Gesture Recognition

Due to the lack of a widely accepted and standardised gesture language, there are two main ways to address this problem: either by developing a universal gesture set or by allowing users to specify custom gestures. Choosing a gesture set might be difficult because gestures heavily depend on culture and individual preferences. Being right- or left-handed is the most evident personal preference, but there are many others that influence natural motions. As a result, the suggested method may be put into practise to adjust to user preferences, either by allowing users to change common gestures or by letting them construct their own unique gesture sets.

Response time was another important system component that needed to be properly taken into account. The activities associated with a user's gesture must be carried out relatively immediately after the user enters it into the system. The amount of memory and CPU performance that a system has access to varies significantly on the mobile device platform that it is running on. Even though the most recent generation of mobile devices, such as smartphones, game consoles, and tablets, boasts powerful processors and other advanced features that, until a few years ago, belonged to desktop computers, making them capable of running complex and computationally demanding applications, even today's most advanced models have limitations that slow down their response due to their size and battery needs. Therefore, during all of the design stages, we gave significant consideration to minimal resource utilisation.

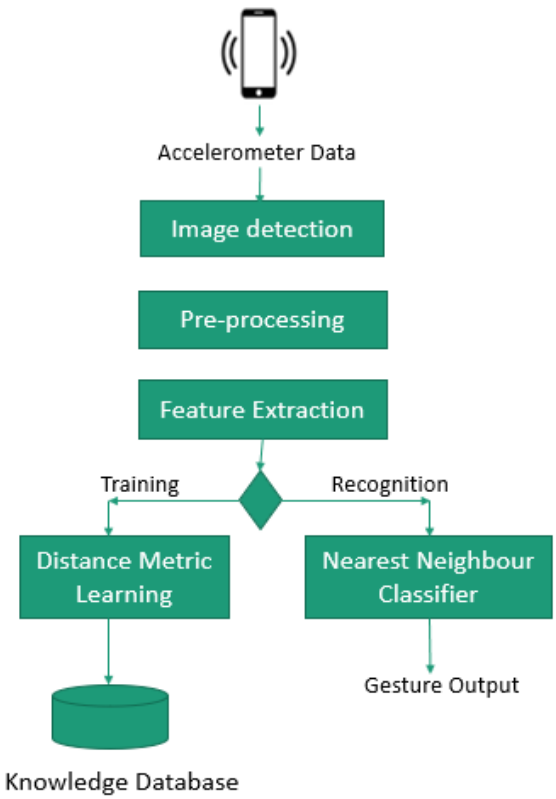

Fig 4: Gesture recognition flowchart

A mobile device having a built-in three-dimensional accelerometer is given to users, such as a smartphone. The system is made up of a knowledge database that keeps track of various sets of gestures and the activities that go along with them, as well as a gesture recognizer algorithm that uses the tracking information gathered from the user to identify the gestures. Every time a gesture is made by the user, the accelerometer sensor detects it and records it. The noise from the acceleration data is then removed, and after passing through a feature extraction module, a matching feature vector is created. In teaching mode, the gesture sample feature vector is only recorded to the database with a suitable label attached for later usage, but in recognition mode, it is processed via a in addition to the classifier component, which uses the knowledge database's pre-set multiple sets of gestures to learn the distance metric and select the most likely gesture. Finally, the user is shown the results of the gesture recognition process, and the necessary actions are carried out.

IV. IMPLEMENTATION

A DGMN prototype has been produced. The Grove ADXL345 3-axis accelerometer, the Grove serial MP3 player with WT5001 chip, the loudspeaker, the Grove vibration motors module, and the Grove HC-05 Bluetooth module are utilised to build the HWD in our prototype. The vehicular radio interface is implemented by the ITRI WAVE Communication Unit (IWCU), which has two IEEE 802.11p interfaces and one Ethernet connection. The warning notification in the DBMW can transmit UDP packets using standard socket APIs like sendto() and recvfrom(), and the IWCU can convert UDP packets into WAVE short messages (WSMs). An Android smartphone's camera utilises OCD to recognise the lane markings on the road, determine how much the lane markings vary in slope, and assess the severity of lane departure.

Bluetooth and Wi-Fi, respectively, are used to link the IWCU and HWD to the Android phone. A WiFi access point is connected to the Ethernet port of the IWCU in order to interact with the Android smartphone. The IEEE 802.11p interfaces' WAVE/DSRC mode is chosen for communication with roadside machinery and nearby automobiles. The Open Computer Vision (OpenCV) library is used to recognise lane lines through edge and line detection, and the Android smartphone's graphical user interface shows the current location of the vehicle's lane, the driver's level of lane deviation and anomaly, and a warning message for risky driving. The realised HWD is made up of a sports helmet, an Arduino development board, a Bluetooth connection module, a 3-axis accelerometer, etc.

We use three Android smartphones placed on various model cars to mimic traffic flows on a road stretch with four lanes (two lanes in each direction). Because the driver's level of irregularity is low, no DGMN message is received when the first car in our experiment utilises the smartphone camera to determine its placement in the lane and the degree of aberrant deviation. The second vehicle recognises the driver's high level of irregularity, much like the first, but no DGMN alarm is sent since it also recognises the driver's amount of normal deviation. The third vehicle, in contrast, sends DGMN alerts to the first and second cars

because it can simultaneously detect a high level of driver abnormality and a high level of anomalous vehicle deviation.

Fig 5: Notification Example

Utilizing the Android sensor framework, it is possible to acquire accelerometer sensor data on the Android platform. A standalone programme was run to obtain the sensor data, and it stored the information to the SD card of the smartphone. An average sampling rate of around 60 Hertz was used for the output signal. It should be emphasised, however, that the data always includes some degree of measurement error, as with all equipment used in the actual world. Additionally, the factory calibration may not be consistent across all created sensors due to variations in the manufacturing process. The sensor data, on the other hand, need to be consistent across all devices and should only change little.

The acceleration vectors underwent a threshold filter as part of the processing stage in order to exclude any comparable vectors from the input data. When the data comes from a normal hand movement, subsequent data vectors are essentially similar due to the accelerometer's great sensitivity and relatively high sampling rate. As a consequence, the amount of data may be drastically decreased by deleting specific vectors from the input data set, accelerating subsequent processing stages and lowering memory requirements. A straightforward Euclidian distance was calculated between the current and prior vectors as a comparison of similarity.

To accommodate the erratic accelerometer sample rate brought on by the Android framework's implementation of the sampling process, the obtained signal was further linearized. The data linearization procedure includes selecting a desirable regular sampling rate and using linear interpolation to fill in all of the signal's gaps.

The nearest sampled data point before and after the intended sampling time was located, and the linearized value was determined by extrapolating what the value of the desired sample time would have been. The mean and minimum time differences between succeeding measurements were computed using a software to ensure that not too much data was interpolated, which may have led to a misleading replica of the original signal. The total dataset's arithmetic average of these two values was then calculated and examined in order to give a broad recommendation for what would be the best sampling rate.

V. RESULT

The experimental setup and findings are provided in this part to demonstrate how well unsafe driving may be detected using both DGMN and currently used approaches. To calculate the detection success rates and false alarm rates of sign sequence matching , 8-space pattern matching, and 32-space DGMN (using 32-space LCS matching), we utilise the DGMN system that has been constructed and is based on Arduino-based HWD and Android-based OCD. In our experiments, 100 abnormal and 100 normal activities are carried out as sensed motion feature vectors (measured in real time), where normal activities include the driver's head turning to the right and left, bending, raising, and nodding. 200 sampling data of anomaly activities (i.e., doze, drunk, and distracted) are adopted as target feature vectors (captured in advance), and 100 anomaly and 100 normal activities are performed. The transformation of each activity into the 13 feature values in a sliding-window motion feature vector. A risky driving incident occurs and is detected within one second of each other.

Here it begin by contrasting the detection success rates and false alarm rates of 32-space DGMN and 8-space pattern matching using various similarity criteria (i.e., the quantity of feature values to be matched), as shown in Figs. 6 and 7, respectively.

It can be shown that when the similarity thresholds are set to 8 or 10, respectively, 32-space DGMN and 8-space pattern matching produce high detection success rates and low false alarm rates. This is so because abnormally low similarity thresholds result in low detection accuracy for anomalous activities, whereas excessively high similarity thresholds result in low detection accuracy for typical activities. However, a higher similarity threshold entails a tradeoff between a lower false alarm rate and a potential drop in detection accuracy.

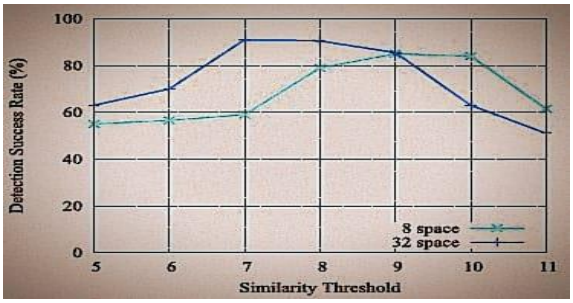

Fig 6: Detection accuracy comparison with various similarity levels

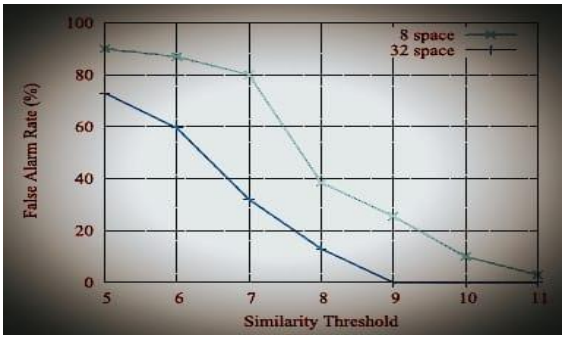

Fig 7: False alarm rates with various similarity levels are compared

In instance, at all similarity criteria, the false alarm rates of 32-space DGMN are significantly lower than those of 8-space pattern matching. It is possible to summarise 8-space pattern matching and 32-space DBMW's detection success rates and false alarm rates. With a similarity threshold of 8, 32-space DBMW has a high detection success rate of 90.5% and a low false alarm rate of 13.0%, but with a similarity threshold of 10, 8-space pattern matching has a high detection success rate of 84.5 % and a low false alarm rate of 10.0%.

VI. CONCLUSIONS

To assess the system's strength and feasibility, this DGMN prototype was built. It comprises of a wearable device with an Arduino processor and an Android-based sensor device. Experiments have shown that DGMN outperforms presently employed methods and can significantly improve the detection accuracy and false alarm rates of unsafe driving behaviours. The driver behaviour monitoring and warning system was developed to increase the safety of all road users, including automobiles, pedestrians, and drivers. With the use of wearable technology and the acceleration data from head movements, our method can determine the driver's condition. By utilising image sensors, our framework measures the vehicle's lane departure by analysing the power spectral density of lane line slope changes in the located lane. Based on the driver's recognised head motion and the vehicle's measured lane departure, our system may send alerts about potentially dangerous driving to nearby vehicles and pedestrians through IoV communications. Our system, for instance, assists in averting potential accidents or collisions as soon as possible by letting vehicles and pedestrians know when dangerous drivers are close.

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