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An Effective Bio-Signal-Based Driver Behavior Monitoring System Using a Generalized Deep Learning Approach

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ABSTRACT Recent years have seen increasing utilization of deep learning methods to analyze large collections of medical data and signals effectively in the Internet of Medical Things (IoMT) environment. Application of these methods to medical signals and images can help caregivers form proper decision-making. One of the important IoMT medical application areas includes aggressive driving behaviors to mitigate road incidents and crashes. Various IoMT-enabled body sensors or camera sensors can be utilized for real-time monitoring and detection of drivers' bio-signal status such as heart rate, blood pressure, and drivers' behaviors. However, it requires a lightweight detection module and a powerful training module with real-time storing and analysis of drivers' behaviors data from these medical devices to detect driving behaviors and provides instant feedback by the administrator for safety, gas emissions, and energy/fuel consumption. Therefore, in this paper, we propose a bio-signal-based system for real-time detection of aggressive driving behaviors using a deep convolutional neural network (DCNN) model with edge and cloud technologies. More precisely, the system consists of three modules, which are the driving behaviors detection module implemented on edge devices in the vehicle, the training module implemented in the cloud platform, and the analyzing module placed in the monitoring environment connected with a telecommunication network. The DCNN model of the proposed system is evaluated using a holdout test set of 30% on two different processed bio-signal datasets. These two processed bio-signal datasets are generated from our collected bio-signal dataset by using two different time windows and two different time steps. The experimental results show that the proposed DCNN model achieves 73.02% of validation accuracy on the processed dataset 1 and 79.15% of validation accuracy on the processed dataset 2. The results confirm the appropriateness and applicability of the proposed deep learning model for detecting driving aggressive behaviors using bio-signal data.

INDEX TERMS Internet of Medical Things (IoMT), bio-signal, aggressive driving behaviors, deep convolutional neural networks (DCNNs), cloud computing, Raspberry Pi.

I. INTRODUCTION

It has been established that the behavior of drivers determines road safety to a great extent [1]. Moreover, many road accidents have been attributed to the driver's behavior in various places in the world [2]. A survey on road safety has revealed that every year 1.3 million fatalities are recorded worldwide, as well as 50 million recorded injuries [3]. Road accidents have also been ranked as the leading cause of death among young people between 15 and 29 years of age [4]. In worrying estimates, the World Health Organization (WHO) reported that traffic accidents will account

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for the third leading killer after cardiovascular and mental illnesses. This has not only affected many lives and taken others but has also increased the economic burden. For example, the United States alone recorded medical costs used in the treatment of accident fatalities as about $99 billion in 2010 [5]. Besides reducing the number of accidents and consequently the amount of money spent in treating road accident fatalities, targeted behavior change by drivers while using the road will lower the amount of fuel consumed and the level of gas emitted. This is in addition to improving road safety [6]. Therefore, the goal of driver behavior profiling is to analyze and enhance the behavior of the driver and create an environment where energy is efficiently consumed. This goal can be achieved through the utilization of a safe and energy-aware approach to driving.

In analyzing and categorizing the aggressive behavior of the driver, a certain set of data is collected. This includes the speed of the vehicle, the acceleration, the braking, steering, and the location [7]. The information is then passed through computer application models to give the final score on safety for the driver. This whole process is technically known as Driver Monitoring and Analysis. It is also called Driver Behavior Profiling [8]. These data can be collected through the use of several devices. First, sensors mounted on smartphones can be used to collect the data. Second, specialized devices such as monitoring cameras, sensors wearable on the body, or telematics can be used. Previously published work [9]–[11] reveals that data collected from wearable sensors are critical in monitoring the behavior of drivers. Hence, they offer a suitable option for sensors that can collect accurate data necessary for behavior profiling.

The significance of analyzing the behavior of drivers has increased in the recent years, the key reasons including the growing popularity of insurance use in the field of telematics. It has been established that the cost of car insurance has reduced significantly with the advent of such insurance policies as Usage-Based Insurance and Pay-How-You-Drive [12]. These policies have been extensively used in rewarding drivers whose safety scores are high. Hence, behavior profiling has become more useful than just the use of age and other statistics, such as gender and marital status of the drivers. The analysis of the driver's behavior, as analyzed on a real-time basis, has been used extensively in freight management. The owners of freight businesses have been able to understand the behavior of their drivers. Therefore, they can start useful campaigns for safe usage of roads. This has resulted in safer roads and lowered consumption of fuel, besides decreased emission of gas to the environment. In addition, such systems as notifications from smartphone apps can inform the driver when accidents are about to occur as a result of reckless and unsafe driving, hence allowing the driver to take control of the situation.

Authors of many published studies detailing the behavior of drivers [13]–[16] have collected their data using sensors based on smartphones to establish aggressive situations in driving that include high speeding and sudden braking as the primary factors for calculating the driver's safety score. A different study [17] involved use of a vehicle sensor to communicate driving tips besides evaluating the use of fuel to include the data while profiling the driver. Most of the researchers made use of machine learning (ML) algorithms, which are ultimately based on diverse dynamic time warping. Yet, other methods that have been applied are voice recognition and the recurrent neural network (RNN) [18].

In this paper, we propose a bio-signal-based system for real-time detection of aggressive driving behaviors using a deep convolutional neural network (DCNN) model with edge and cloud technologies. This main goal of the paper is achieved with the following contributions:

1) As a result of a lack of public bio-signal datasets of driving behaviors, we provide a public bio-signal dataset for researchers and developers to evaluate their driving behaviors detection methods and models.

2) We propose an effective structure of DCNN model as a feature extractor of bio-signal data instances. The DCNN model is used in the proposed system architecture because it has an ability to represent the features with high dimensions and has a good speed for real-time detection because its convolution layers are not fully connected layers.

3) We evaluate the proposed DCNN model on two different processed bio-signal datasets, generated from the original collected dataset by using two different time windows and two different time steps.

4) We analyze the efficiency and effectiveness of different DCNN models to detect aggressive driving behaviors using the two processed bio-signal datasets.

5) We compare the proposed DCNN model with the traditional ML models using the two different processed bio-signal datasets to show its superiority and effectiveness.

The rest of this paper is structured as follows: Section II presents the related works. Section III provides a summary of the analyses of the driver's behavior and also introduces the DCNN techniques. Section IV outlines and describes the data collection and preprocessing procedure. Section V shows the experimental analysis as well as the results obtained from the experiment. The final Section VI concludes our work and identifies gaps upon which future researchers can focus.

II. RELATED WORK

Research on the behaviors of drivers continues to be published to date. Various studies have been conducted with the use of such data as the status of the vehicle and in the application of both ML and deep learning algorithms. Lee and Jang [19] used data from acceleration and the speed of the vehicle to categorize the behavior of the driver. This included the applications of ML methodologies that included the auto-encoder as well as self-organizing map. Out of the 32 styles of driving used in this study, some of the driving behaviors were found to be dangerous. Chen *et al.* [20] made use of the sensor known as an inertial measuring unit (IMU)

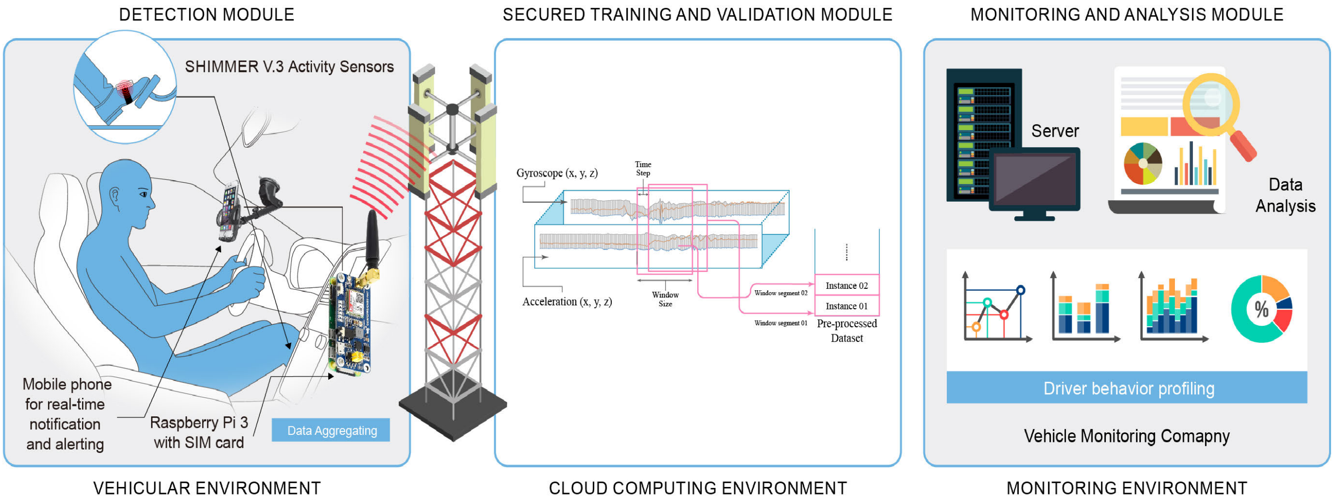

FIGURE 1. Proposed driving behavior monitoring system architecture.

to analyze the behavior of the driver while turning left and turning right. The scholar observed given characteristics to identify the driver during the moment of turning. The data collected for the driver's behavior classification included the following: the acceleration of the vehicle at the end-of-turn axis and the deviation of the given acceleration of the vehicle along the end-of-turn axis. Additionally, data on the raw rate of yaw deviation was used in devising the features used in creating a classifier known as Naïve Bayes. The number of drivers who had their behavior recorded and were monitored throughout the course of the study stood at 12. The monitoring was done using IMU sensors fixed on smartphones that were used by the drivers. The technology used to collect and analyze data to establish the behavior of the driver performed most accurately as regards collecting data along a longitudinal direction. However, it was found to fall short of accuracy when collecting data along the lateral direction.

The data on the vehicle operation that shows how the vehicle was affected as a result of the driver's behavior was challenging to collect [21]. These data were gathered from an on-board diagnostic system (OBD-II), which would then relay the same information to the driver on board through communication by a Bluetooth Low Energy system. Other parameters that have been found useful in data collection, hence aiding the analysis of the driver's behavior, include the status of the vehicle and the information on its operation, as suggested by Martinelli *et al.* [22]. This kind of data was obtained from the OBD-II system. It included 51 categories of information. The categories include the fuel consumption, the position of the accelerating pedal, the steering wheel's angle, the steering speed, and the speed. Information on nine drivers was also analyzed by the use of principal component analysis with the sole aim of deducing their behavior. This addressed the research gap that was posed by the use of the already existing systems that used the information, including the vehicle's status, because it could not communicate real-time data for analysis.

In another work [23], the authors had the primary objective of detecting risky road situations that could potentially lead to accidents. The experiment took into account 36 drivers whose data was collected using simulators that had diverse road conditions such as obstacles with the possibility of causing an accident. A similar approach involved a simulator being used to help drivers avoid accident-causing situations [24]. In this work, the researchers devised a system that used statistical modeling in the prediction of accident risks and consequently informed the driver. Scenarios that the authors in [25] considered included corners and sharp bends on the road and slippery surfaces. They used data collected from nine drivers.

Authors in [26] investigated novice drivers to determine the factors that influenced the behavior of drivers in the first year of road use. They collected data on 62 drivers who were novices as well as their parents' data in real time. They identified 20 scenarios that they then classified into four categories as follows: braking and accelerating category, turning category, lane handling category, and speeding category, in relation to their level of risk. The authors concluded that the risk of causing accidents was reduced when the novice drivers were supervised by their parents and when they received feedback regarding the level of risk while on the road.

III. AGGRESSIVE DRIVING BEHAVIORS DETECTION SYSTEM

A. SYSTEM ARCHITECTURE

This system is designed to detect dangerous behaviors that increase the risk of accidents. Such behaviors noted include high acceleration, sudden braking, sudden change of lanes to the right, and sudden change of lanes to the left, all on a real-time basis. In Figure 1, the architecture of the proposed

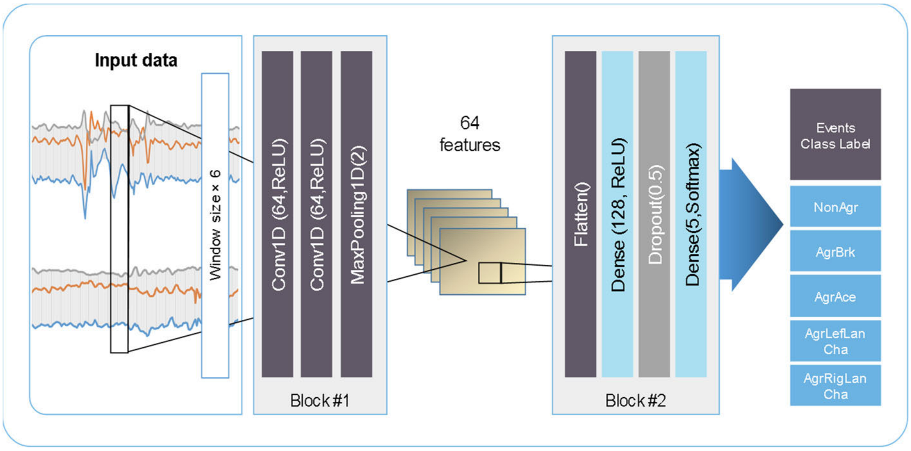

FIGURE 2. The structure of proposed DCNN model.

system is shown. The architecture consists of three main modules: the detection module, the training and validation module, and the monitoring and analysis module. In the detection module, the data are obtained and collected from wearable SHIMMERv.3 sensors. The driver wears the sensor on the right foot. All signals are transferred through Wi-Fi signals to a Raspberry Pi 3 equipped with a SIM card.

In the data aggregation module, drivers' aggressive data are aggregated prior to transmitting and offloading to the cloud. This task is conducted through the use of Raspberry Pi devices equipped with a SIM card. To enhance the transmission speed, the aggregation module uses a threshold level for reducing congestion of the network. More precisely, normal driving data of the driver are aggregated based on the selected threshold value, while the data classified as aggressive are sent immediately with no delay. The following algorithm elaborates the steps of the aggregation module:

Raspberry Pi device receives the gyroscope and acceleration signals from the SHIMMER sensors.

1. ML module to classify the signal based on the trained model.
2. If records are classified as aggressive driving, then flag the data as high priority and offload the data to the cloud.
3. If records are classified as normal driving, then aggregate the collected data and offload them to the cloud based on the network connectivity.

B. PRPOSED DEEP LEARNING MODEL

Figure 2 represents the proposed deep convolutional neural network (DCNN) architecture, which is used in our cloud computing environment. To make the model applicable in limited IoT devices such as Raspberry Pi, the proposed DCNN architecture is designed to be lightweight. It consists mainly of two blocks for feature representation and classification. The first block receives an input shape of 2400 attributes. It includes two convolution layers of 1-D inputs with ReLU activation function. The number of convolution kernels of the two convolution layers is 64, and the filter length is 3. These two convolution layers are followed by a 1-D max pooling layer of pool size 2. After the max pooling layer, the model contains a flatten layer, a dense layer of 128 neurons with ReLU activation function, a dropout layer of drop rate 0.5, and a dense fully connected layer of 5 neurons with a softmax activation function. The number of neurons of this dense layer matches the number of classes. All convolutional layers deploy a Rectified Linear Unit (ReLU) as an activation function. ReLU is a highly simple and non-liner function that is known to be fast in training large networks, while the dropout layer can handle the overfitting issue by regulating the network.

The proposed DCNN model is designed to have a low cost as a result of the limited number of learnable parameters that are fit for our system. The third component of our system is a module for monitoring and analysis, where the overall data of drivers' behaviors are analyzed and profiled for monitoring by the vehicles companies.

IV. DATA COLLECTION AND PREPROCESSING

For the purpose of this study, real-world driving behavior data were gathered from bio-sensor data on specific driving behaviors. The body sensor was used in recording and collecting data, while the drivers were involved in a particular behavior of driving. We made a note of both the starting and ending times of the driving behaviors with the sole aim of obtaining accurate data for the experiments. In the section that follows, the details of the data collection are given, with an explanation of how data pre-processing are performed.

A. DATA COLLECTION

Our collected aggressive driving behaviors (ADBs) dataset[1] involves three different car trips that averaged 70 minutes. The tools and settings used for collecting the dataset were as follows: (I) The vehicle used was the Hyundai Elantra

[1] https://github.com/abdugumaei/ADBs-Dataset

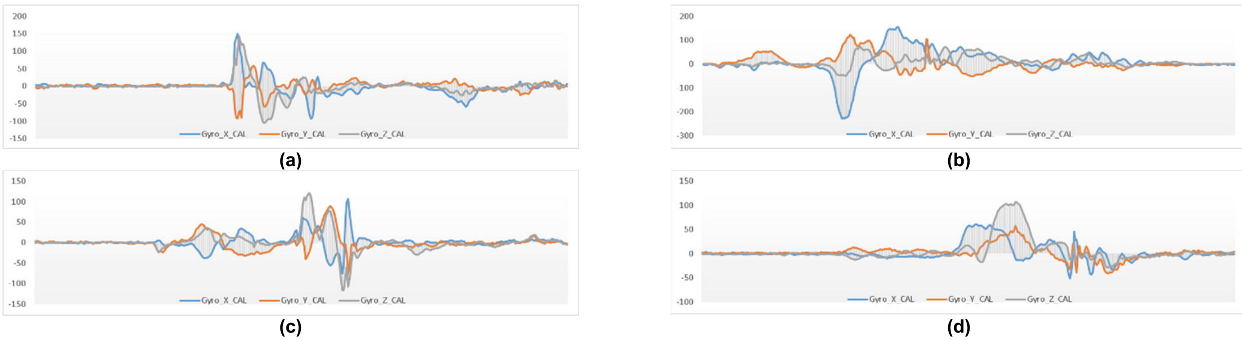

FIGURE 3. Example of a time series of three axis gyroscope recorded data for (a) aggressive acceleration (b) aggressive braking (c) aggressive right lane change and (d) aggressive change lane left.

Model of 2020; (II) The Shimmer Version 3 wearable body sensors were used; (III) The body sensors were worn by the driver on the right and left wrists, left arm, and right foot; IV) The rate of sampling of the sensors used stood at 100 HZ; (V) The drivers involved in the data collection each had driving experience of 10 years; and finally, (VI) The roads on which the driving behaviors were tested were dry and had asphalt for pavement, and the weather in which the experiment took place was sunny. The kinds of driving behaviors used in this data collection are the most critical behaviors that can lead to serious accidents for drivers. Our primary goal was to come up with a representation of real-world driving behaviors: aggressive braking, aggressive increased acceleration, aggressive turning, and changing lanes.

The driving class names, numbers, and labels of behaviors are shown in Table 1. The number of samples for each driving behavior and the total number of samples of the ADBs dataset are listed in Table 2. An example of ADBs dataset samples is shown in Table 3. The wearable sensor is used in measuring speed in meters per unit second squared (m/s^2)

TABLE 1. The driving behavior classes with numbers, names and labels.

Behavior Class Number	Behavior Class Name	Behavior Class Label
0	Non-aggressive	NonAgr
1	Aggressive breaking	AgrBrk
2	Aggressive acceleration	AgrAce
3	Aggressive left lane change	AgrLefLanCha
4	Aggressive right lane change	AgrRigLanCha

TABLE 2. ADBs dataset total samples.

Behavior Class Label	Number of Samples
NonAgr	24000
AgrBrk	24000
AgrAce	24000
AgrLefLanCha	24000
AgrRigLanCha	24000
Total	**120000**

that is applied on the vehicle with the inclusion of gravitational force. Besides, the accelerometer sensors offer a 3-axis (x, y, z) of the temporal series that has the precision of a nanosecond in the sensor coordinate standard system in relation to the device used. The example of the data from a gyroscope is given in Figure 3, while Figure 4 represents an example of acceleration data.

B. DATA PRE-PROCESSING

These data are then conveyed to the training and validation module in the cloud. To convert the data points of each behavior into signal patterns, we preprocessed these data points by two configurations, the first configuration having a window size of 400 (4 seconds) and a time step of size 40 (0.4 seconds). In this configuration, the collected dataset of 120,000 data samples with six attributes are processed to generate (120,000/20) − (200/20) instances × (200 × 6) attributes = 5,990 instances × 1,200 attributes. The second configuration has a window size of 200 (2 seconds) and a time step of size 20 (0.2 seconds). Consequently, the collected dataset of 120,000 data points and six attributes is processed to have (120,000/40) − (400/40) instances × (400 × 6) attributes = 2,990 instances × 2,400 attributes. By these two configurations, the ADBs dataset is processed to generate two processed datasets: processed dataset 1, which consists of 5,990 instances, and processed dataset 2, which has 2,990 instances. The number of instances per class of processed datasets 1 and 2 is given in Table 4.

V. EXPERIMENTS AND DISCUSSION

In this section, a set of experiments are conducted on our collected ADBs dataset. The results of these experiments are computed based on different performance evaluation measures, such as accuracy, F1-score, recall, precision, and confusion matrices. Confusion matrices are tables used to compute the results of other performance measures in the experimental evaluation of the models. The other performance evaluation measures are calculated using the true positive (TP), true negative (TN), false positive (FP), and false negative (FN) of the instances resulting in the confusion matrices.

TABLE 3. Some data samples of ADBs dataset.

Timestamp	Accel_X	Accel_Y	Accel_Z	Gyro_X	Gyro_Y	Gyro_Z	Class_Number
1.00E+00	-2.13043	5.880435	8.956522	0.229008	2	-1.17557	0
2.00E+00	-2.01087	2.217391	10.03261	1.068702	0.610687	-1.26718	0
3.00E+00	-1.84783	1.934783	10.07609	2.748092	1.099237	-1.32824	0
4.00E+00	-1.86957	2.217391	9.956522	3.022901	1.572519	-0.79389	0
5.00E+00	-1.97826	2.434783	9.902174	1.251908	1.251908	-0.61069	0
2.40E+04	-1.01087	2.815217	10.25	-2.50382	0.564885	-1.49618	1
2.40E+04	-0.93478	2.76087	10.30435	-4.06107	0.824427	-1.63359	1
2.40E+04	-1.01087	2.586957	10.3913	-3.72519	0.656489	-1.1145	1
2.40E+04	-0.97826	2.532609	10.33696	-2.82443	0.885496	-1.52672	1
2.40E+04	-0.97826	2.521739	10.29348	-2.15267	1.160305	-2.06107	1
4.80E+04	-4.48913	4.815217	6.869565	3.770992	-4.48855	-0.06107	2
4.80E+04	-4.55435	5	6.717391	2.70229	-5.17557	-0.24427	2
4.80E+04	-4.56522	5.217391	6.956522	2.641221	-5.38931	-1.22137	2
4.80E+04	-4.78261	5.413043	7.293478	2.503817	-4.0458	-1.60305	2
4.80E+04	-4.88043	5.478261	7.369565	4.931298	-1.46565	-0.27481	2
7.20E+04	-3.91304	4.423913	8.23913	2.096947	-2.89359	0.329771	3
7.20E+04	-4.06522	4.630435	8.26087	0.921374	-2.81725	0.116031	3
7.20E+04	-4	4.48913	8.217391	-0.3916	-2.46611	-0.25038	3
7.20E+04	-3.8913	4.315217	8.130435	-1.42977	-1.22947	0.207634	3
7.20E+04	-4.02174	4.315217	8.152174	-1.58244	0.114046	0.482443	3
9.60E+04	-3.77174	0.467391	8.423913	0.132824	0.149466	-0.67069	4
9.60E+04	-4.03261	0.423913	8.423913	-0.01969	-0.72214	0.454351	4
9.60E+04	-3.84783	0.51087	8.434783	0.458473	-0.78122	1.145038	4
9.60E+04	-3.76087	0.456522	8.434783	1.135878	0.720153	0.812824	4
9.60E+04	-4	0.5	8.445652	0.538321	-0.11649	0.641985	4

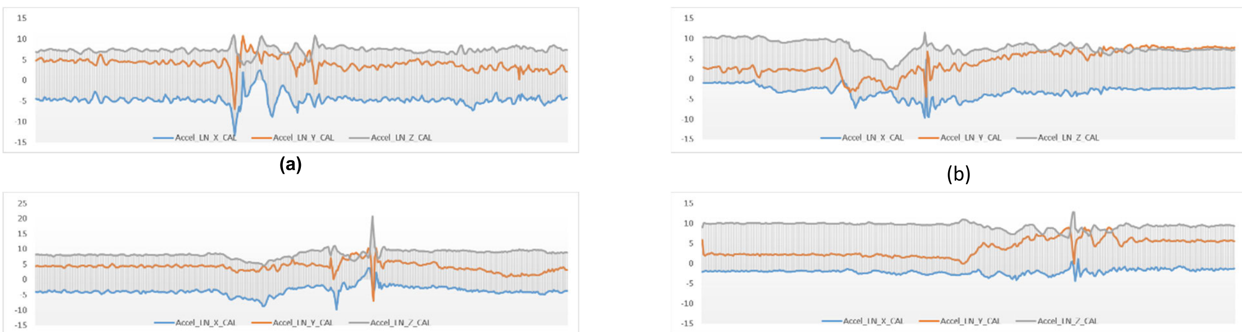

FIGURE 4. Example of a time series of three axis accelerometer recorded data for (a) aggressive acceleration (b) aggressive braking (c) aggressive right lane change and (d) aggressive change lane left.

The equations used for computing these evaluation measures are written as follows.

$$\text{Accuracy} = \frac{(\text{TP} + \text{TN})}{(\text{TP} + \text{TN} + \text{FP} + \text{FN})} \tag{1}$$

$$\text{Precision} = \text{TP}/(\text{TP} + \text{FP}) \tag{2}$$

$$\text{Recall} = \text{TP}/(\text{TP} + \text{FN}) \tag{3}$$

$$\text{F1} - \text{measure} = \frac{2 \times (\text{Precision} \times \text{Recall})}{(\text{Precision} + \text{Recall})} \tag{4}$$

In all experiments, the parameters of the DCNN model are set to have the values described in the system architecture. The effects of using different numbers of layers and different dropout rates will be given in a subsection after presenting the experimental results of the proposed model.

To organize the experiments of the work, two groups of the experiments are presented according to the configurations used for processing the dataset. The first group is the experiments conducted on the processed dataset 1 that is generated with a 0.2-second time step (20 data samples of overlapping between window segments of behaviors signals) and 2-second window time segment (200 data samples that represent each instance of each behavior). In addition, the second group of the experiments are performed on processed dataset 2, which is also generated with a 0.4-second time step (40 data samples) and 4-second window time segment (400 data samples). In both groups, the processed datasets are divided arbitrarily based on the holdout technique, in which 70% is used for training and 30% is applied for validation and testing the models. The two groups of the

TABLE 4. Number of instances for both processed datasets 1and 2.

Behavior Class Label	Processed dataset 1	Processed dataset 2
NonAgr	1201	601
AgrBrk	1200	600
AgrAce	1200	600
AgrLefLanCha	1194	594
AgrRigLanCha	1195	595
Total	**5990**	**2990**

experiments are explained and discussed in the following subsections.

A. EXPERIMENTS ON PROCESSED DATASET 1

This subsection introduces the evaluation results on validation and test sets of processed dataset 1. In the first experiment, 4,193 instances (70%) are used for training the model, and 1,797 instances (30%) are applied for validating and testing the model. The distribution of instances in training and test sets is given in Table 5. Each instance has 1,200 data values as attributes.

TABLE 5. Distribution of instances in training and test sets of processed dataset 1.

Behavior Class Label	Train Instances	Test Instances	Total
NonAgr	840	361	1201
AgrBrk	823	377	1200
AgrAce	834	366	1200
AgrLefLanCha	850	344	1194
AgrRigLanCha	846	349	1195
Total	**4193**	**1797**	**5990**

Figures 5 and 6 show the results of accuracy and loss for the training and validation sets during the 100 epochs of training phase. The confusion matrix that contains the number of corrected classified instances of maximum validation accuracy of the model is given in Figure 7. The results of other evaluation measures can be computed from the confusion matrix and are shown in Table 6.

From Table 6, we can see that the DCNN model achieves 77.57% of maximum accuracy on the validation set of processed dataset 1. In addition, we can notice that the maximum number of correctly classified instances is for aggressive breaking behavior (313 from 366) and aggressive right lane change behavior (313 from 349).

This means that these two behaviors are distinguishable from other behaviors. The minimum number of correctly classified instances is for nonaggressive behavior (212 from 361) because the data points of these behaviors are overlapped with the data points of the other behaviors.

The second experiment selects 839 instances as a validation set from the 4,193 instances of the training set, to result in 3,354 instances (50%) for the training set, 839 instances (20%) for the validation set, and 1,797 instances for the test set (20%) to evaluate the model as unseen examples.

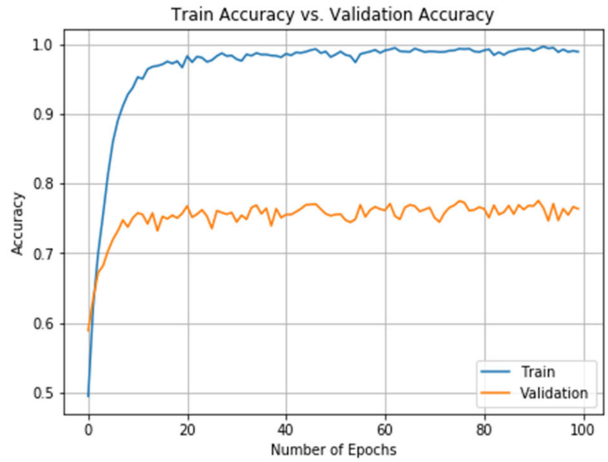

FIGURE 5. Train accuracy vs. validation accuracy of first experiment on processed dataset 1.

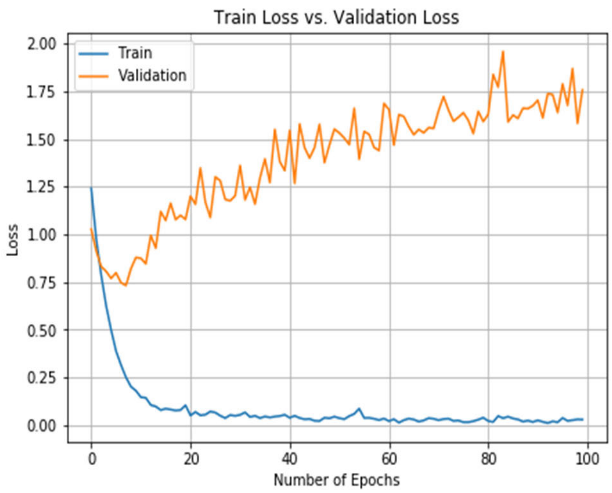

FIGURE 6. Train loss vs. validation loss of first experiment on processed dataset 1.

TABLE 6. Evaluation results of accuracy, F1-score, precision, and recall of validation set for processed dataset 1.

Behavior Class Label	Precision	Recall	F1-score	Accuracy
NonAgr	0.739	0.634	0.683	77.57%
AgrBrk	0.707	0.830	0.763	
AgrAce	0.749	0.749	0.749	
AgrLefLanCha	0.796	0.770	0.783	
AgrRigLanCha	0.907	0.897	0.902	
Micro avg.	0.776	0.776	0.776	
Macro avg.	0.779	0.776	0.776	
Weighted avg.	0.778	0.776	0.775	

Figures 8 and 9 illustrate the training and validation accuracy and loss in the training process of the 100 epochs.

From Figures 8 and 9, we see that accuracy and loss of the validation set are still in a specific range. The validation

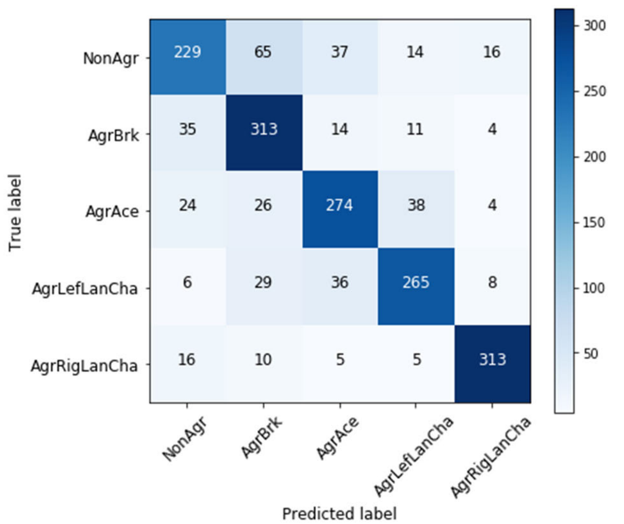

FIGURE 7. Confusion matrix of first experiment on processed dataset 1.

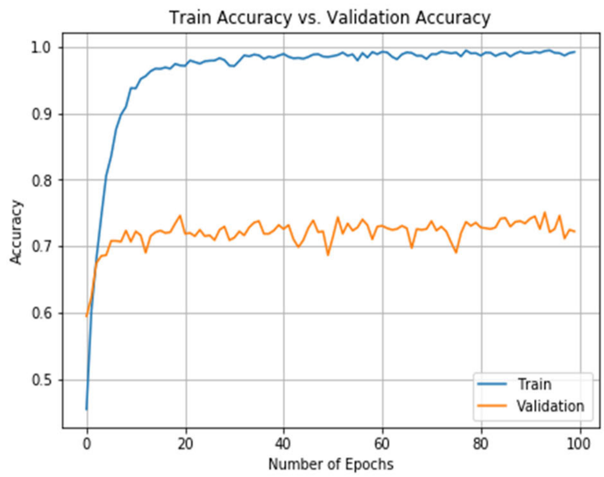

FIGURE 8. Training accuracy vs. validation accuracy of second experiment on processed dataset 1.

accuracy is in a range more than 70% and less than 80%. In addition, the validation loss is less than 0.2 in most epochs. Figure 10 shows the confusion matrix of the test set for the model that has the maximum validation accuracy in the training phase. Table 7 presents the results of the other evaluation measures obtained from the confusion matrix.

In Table 7, the DCNN model achieves 71.95% of accuracy and 71.4% of F1-score on the unseen instances of the test set for processed dataset 1.

In addition, the confusion matrix in Figure 10 shows that the maximum number of correctly classified instances is for aggressive breaking behavior (283 from 366) and aggressive right lane change behavior (321 from 349). This confirms that these two behaviors can be distinguishable from other behaviors. In contrast, the Non-aggressive behavior has a minimum number of correctly classified instances (173 from 361).

FIGURE 9. Training loss vs. validation loss of second experiment on processed dataset 1.

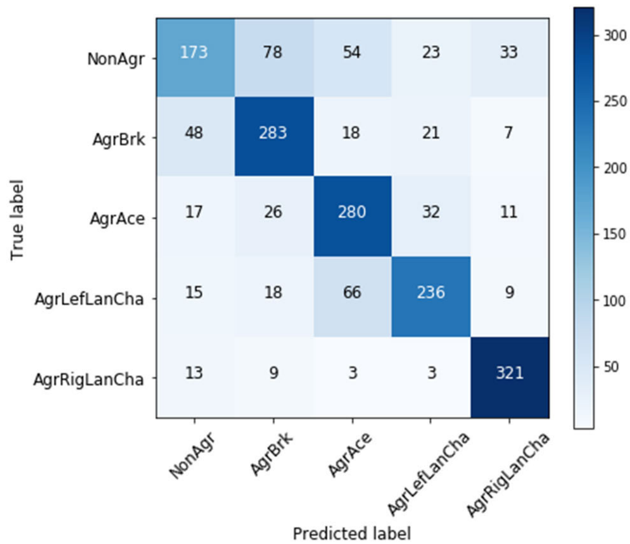

FIGURE 10. Confusion matrix of second experiment on processed dataset 1.

TABLE 7. Evaluation results of accuracy, F1-score, precision, and recall of test set for processed dataset 1.

Behavior Class Label	Precision	Recall	F1-score	Accuracy
NonAgr	0.650	0.479	0.552	
AgrBrk	0.684	0.751	0.716	
AgrAce	0.665	0.765	0.712	
AgrLefLanCha	0.749	0.686	0.716	
AgrRigLanCha	0.843	0.920	0.879	71.95%
Micro avg.	0.720	0.720	0.720	
Macro avg.	0.718	0.720	0.715	
Weighted avg.	0.717	0.720	0.714	

B. EXPERIMENTS ON PROCESSED DATASET 2

In this group of experiments, we evaluate the proposed model on processed dataset 2. This dataset is divided randomly into two sets: 70% training set and 30% test set. In the first experiment of this group, 2,093 instances are used for training the model and 897 instances are utilized for validating and testing the model. The distribution of instances in the training and test sets is shown in Table 8. Each instance has 2,400 data values as attributes.

TABLE 8. Distribution of instances in training and test sets of processed dataset 2.

Behavior Class Label	Train Instances	Test Instances	Total
NonAgr	425	176	601
AgrBrk	414	186	600
AgrAce	415	185	600
AgrLefLanCha	419	175	594
AgrRigLanCha	420	175	595
Total	**2093**	**897**	**2990**

Figures 11 and 12 show the results of accuracy and loss for the training and validation sets during the 100 epochs of the training phase. The confusion matrix that contains the number of correctly classified instances of maximum validation accuracy of the model is given in Figure 13. The results of other evaluation measures can be computed from the confusion matrix and are shown in Table 9.

TABLE 9. Evaluation results of accuracy, F1-score, precision, and recall of validation set for processed dataset 2.

Behavior Class Label	Precision	Recall	F1-score	Accuracy
NonAgr	0.685	0.705	0.695	79.15%
AgrBrk	0.763	0.726	0.744	
AgrAce	0.814	0.805	0.810	
AgrLefLanCha	0.815	0.829	0.822	
AgrRigLanCha	0.882	0.897	0.890	
Micro avg.	0.792	0.792	0.792	
Macro avg.	0.792	0.792	0.792	
Weighted avg.	0.792	0.792	0.791	

From the results in Figures 11 and 12, we can see that the gaps between accuracy and loss between the training and validation sets are reduced. Moreover, from Table 9, we can observe that the DCNN model achieves 79.15% of accuracy and 79.2% of F1-score micro and micro averages when using the testing set to validate the model.

In the second experiments of this group, processed dataset 2 is divided into three sets: the training set contains 1,674 instances (50%), the validation set consists of 419 instances (20%), and the test set has 897 instances (30%). Here, we train and validate the DCNN model on the training set validation sets, then the trained model is evaluated on unseen instances of test set. Figures 14 and 15 show the progress of accuracy and loss for train and validation sets through the 100 epochs of the training process.

TABLE 10. Evaluation results of accuracy, F1-score, precision, and recall of Test set for processed dataset 2.

Behavior Class Label	Precision	Recall	F1-score	Accuracy
NonAgr	0.572	0.631	0.600	73.02%
AgrBrk	0.685	0.667	0.676	
AgrAce	0.735	0.719	0.727	
AgrLefLanCha	0.779	0.766	0.772	
AgrRigLanCha	0.905	0.874	0.890	
Micro avg.	0.730	0.730	0.730	
Macro avg.	0.735	0.731	0.733	
Weighted avg.	0.734	0.730	0.732	

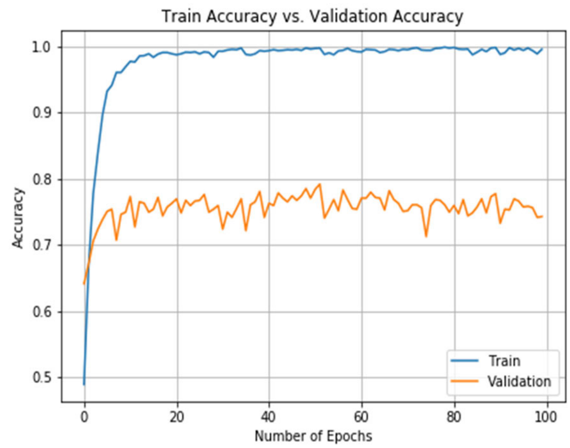

FIGURE 11. Training accuracy vs. validation accuracy of first experiment on processed dataset 2.

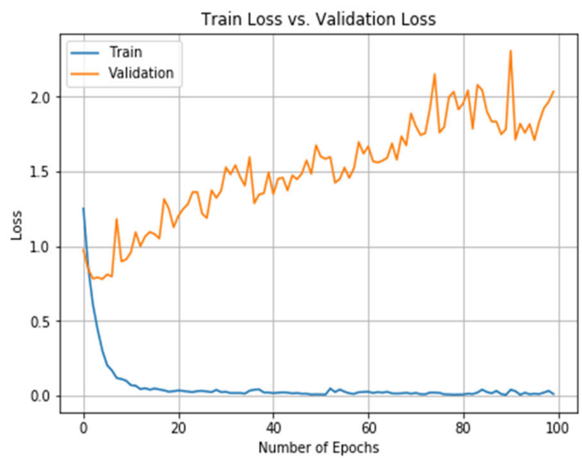

FIGURE 12. Training loss vs. validation loss of first experiment on processed dataset 2.

Figure 16 presents the confusion matrix, and Table 10 gives the results of evaluation measures on the test set.

From the results of the first and second experiments on processed dataset 1 and 2, we notice that DCNN mode works better on the signals of driver aggressive behaviors that are processed with window size 400 and time step 40 than the

TABLE 11. The results of validation accuracy and averaged classification time of different DCNN models on processed dataset 2.

Model	Number of convolution layers	Number of Convolution Kernels	Drop Rate	Validation Accuracy	Averaged Classification Time
Model 1 (Proposed Model)	2	64, 64	0.5	79.15%	4.473
Model 2	3	64, 64, 64	0.5	78.15%	11.188
Model 3	4	64, 64, 64, 64	0.5	65.89%	6.548
Model 4	4	64, 64, 128, 128	0.5	72.80%	20.786
Model 5	2	64, 64	0.25	75.14%	4.557
Model 6	2	64, 64	0.15	73.36%	4.545
Model 7	2	128, 128	0.5	76.48%	10.297
Model 8	2	32, 32	0.5	77.26%	2.141
Model 9	2	16, 16	0.5	74.25%	1.170

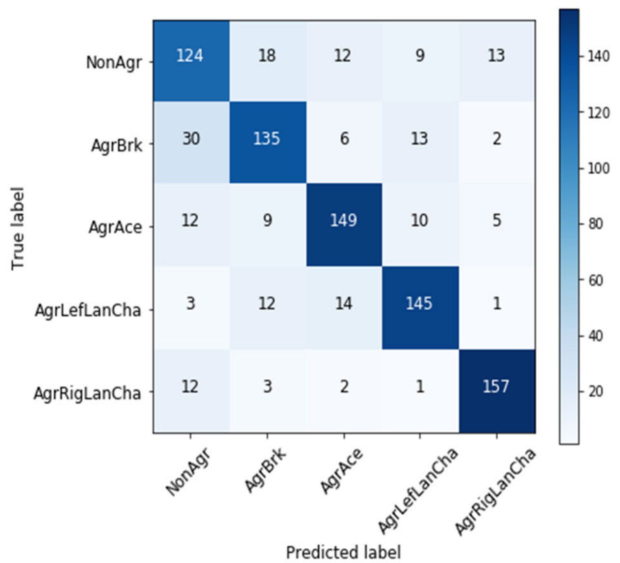

FIGURE 13. Confusion matrix of first experiment on processed dataset 2.

TABLE 12. Comparison results of test accuracy and averaged classification time for the proposed DCNN model against the traditional ML modes on processed dataset 1.

Model	Test Accuracy	Averaged Classification Time (in seconds)
AdaBoostClassifier	50.53%	0.203
SVM	58.49%	9.139
KNN	55.04%	19.190
RF	66.33%	0.078
XGB	64.83%	0.141
DT	44.91%	0.02
GaussianNB	41.57%	0.422
Proposed DCNN	71.95%	4.513

signals that are processed with window size 200 and time step 40. The reason for this improvement is that window size 400 is able to represent the aggressive behaviors better than window size 200, and time step 40 better represents the overlap between signals' behaviors.

TABLE 13. Comparison results of test accuracy and averaged classification time for the proposed DCNN model against the traditional ML modes on processed dataset 2.

Model	Test Accuracy	Averaged Classification Time (in seconds)
AdaBoostClassifier	53.40%	0.187
SVM	59.31%	4.495
KNN	45.60%	8.475
RF	65.66%	0.039
XGB	67.89%	0.097
DT	42.59%	0.01
GaussianNB	49.61%	0.337
Proposed DCNN	73.02%	4.357

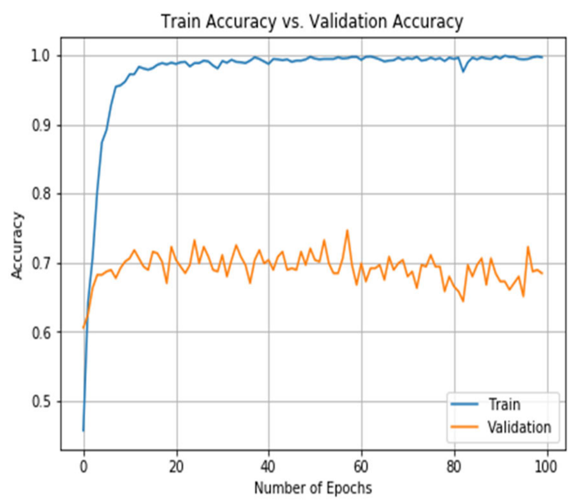

FIGURE 14. Training accuracy vs. validation accuracy of second experiment on processed dataset 2.

C. RESULTS ANALYSIS OF MODEL SELECTION

In this subsection, we conduct some experiments on the model using different numbers of layers and different values of dropout rate. The experiments are performed on processed dataset 2, which is divided into two sets: 70% as training set and 30% as test set. The test set is used to validate the model in the training phase. Different configurations and settings of the proposed model are investigated to justify the selected

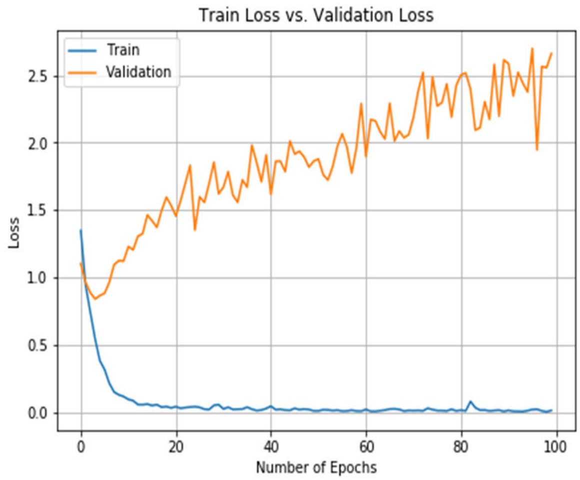

FIGURE 15. Training loss vs. validation loss of second experiment on processed dataset 2.

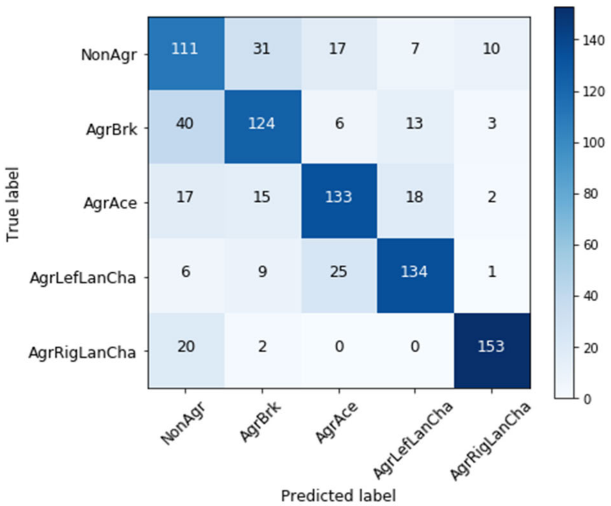

FIGURE 16. Confusion matrix of second experiment on processed dataset 2.

architecture of the proposed model. From the proposed model (model 1), a different set of models is created using different numbers of convolution layers with different convolution kernels and using different drop rates of dropout layer. Then, these models are evaluated based on the results of validation accuracy and averaged classification time. Table 11 shows the results of validation accuracy and averaged classification time of different DCNN models on processed dataset 2.

From the results of Table 11, we can see clearly that the proposed model (model 1) achieves the highest validation accuracy results with acceptable averaged classification time compared to the other deep learning models of different configurations. This justifies the effectiveness of the selected structure and parameters' values of the proposed model.

D. COMPARISON OF ACCURACY RESULTS

This section compares the performance of the proposed model against the traditional ML modes, such as AdaBoost-Classifier, support vector machine, K-nearest neighbors, random forest, extreme gradient boosting, decision tree, and Gaussian Naïve Bayes. In this comparison, the results of test accuracy and averaged classification time are computed using processed dataset 1 and processed dataset 2. Tables 12 and 13 list the performance results of the DCNN model against the traditional ML modes.

From the results of Tables 12 and 13, we can see clearly that the DCNN model outperforms the traditional ML modes in terms of test accuracy. We can notice also that the averaged classification time for the proposed DCNN model is acceptable to be applied for real-time detection of drivers' aggressive behaviors.

VI. CONCLUSIONS

Detecting aggressive driving behavior through a monitoring system can play a vital role in reducing road accidents. The goal is to analyze the driver behavior while driving and to enhance the behavior of the driver to create a healthy driving environment. In this paper, we presented a real-time aggressive driving behaviors detection and monitoring system using body sensors. We collected real-time bio-signal-based aggressive driving behavior data and made it public for researchers and developers. We used a DCNN model with edge and cloud technologies to analyze the collected driving behavior data. The proposed DCNN model was able to represent the features with high dimensions and showed better performance for real-time driving behavior detection as compared to traditional ML models. In the future work, we plan to use other deep learning models with the regularization technique to improve the performance of the proposed driving behaviors monitoring system.

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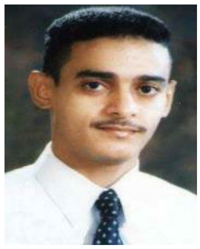

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