Driver Behaviour Detection

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***Abstract*— Driver drowsiness and distraction are the leading causes of road accidents that can have fatal consequences. To mitigate this problem, it is imperative to create information systems that can identify these conditions. Moreover, there are several other factors that can distract drivers while driving, including texting or talking on the phone, adjusting the radio, consuming food or drink, reaching behind, and engaging in conversations with passengers. There are various methods used to address the problem of driver distraction and drowsiness. Some of the commonly used methods are: One effective method in combating driver drowsiness and distraction is through the development of information systems. These systems utilize technologies that can detect signs of driver fatigue and distraction, including monitoring eye movements, head position, and steering behavior using sensors. These systems can alert the driver or take control of the vehicle automatically to avoid potential accidents, Improving the quality of road infrastructure, such as by installing rumble strips, improving road signs' clarity, and enhancing lighting, can assist drivers in remaining attentive and averting potential accidents, By increasing awareness of the risks related to driver distraction and drowsiness, educational and training programs can play a vital role in reducing the occurrence of accidents caused by these factors and Legal measures: Implementing laws and regulations that prohibit the use of mobile phones while driving, require mandatory rest breaks for long-distance drivers, and impose penalties for reckless driving can deter drivers from engaging in dangerous behaviors that can cause accidents. Our ultimate goal is to concentrate on the development of an application capable of identifying driver drowsiness and distraction.**

Keywords— Behavior detection, Deep Learning, feature Extraction, Distraction and Drowsiness Classification

I. Introduction

Every year, approximately 1.3 million people lose their lives as a result of road crashes. Additionally, between 20 and 50 million people sustain non-fatal injuries, many of whom will acquire disabilities due to their injuries. The economic impact of these crashes and injuries is estimated at approximately US $518 billion annually. Human error is the primary cause of nearly 80% of severe traffic collisions, with distracted driving accounting for over 60% of commercial fleet collisions. Common driver distractions include drowsiness, driving under the influence, eating, and texting. In some major countries such as Canada, Australia, France, Portugal, and the USA, road traffic fatalities involving alcohol account for over 30% of all crashes. Driver behavior that is unsafe, encompassing impaired, aggressive, distracted, and speeding driving, is a major cause of road traffic fatalities and injuries globally

A. *Motivation*

A driver assistance system to increase car and road safety. Meanwhile, economical vehicles do not have that kind of system. This fact encourages the development of software that is available to everyone to use while driving to prevent accidents from occurring. The project aims to help computer and artificial intelligence to save lives, reduce the danger of distracted or sleepy drivers on the road and help them to stay focused and alert.

B. *Objective*

The main objective of the project is developing a driver Behavior detection software to help drivers stay safe. To

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achieve that, the system detects whether the driver is drowsy or distracted or doesn't wear a seatbelt, if both eyes are closed for a certain amount of time or the driver doesn't wear the seat belt or distracted, the system plays a loud sound to alert the drivers to stay aware and putting their and others lives in danger.

Our project comprises several steps. The first step involves presenting a detailed description of the project's field, along with a description of existing similar systems. In the second step, we will display a system architecture diagram, along with a detailed description of each module and the CNN model's architecture in the system. In the third step, we will describe in detail all functions, techniques, and algorithms implemented in the system. Additionally, we will explain libraries used in project implementation, datasets and their preprocessing, models building and training, project classes, system integration, UI design, and testing. In the fourth step, we will run the application and provide a complete user guide that shows how to operate the project, including any required third-party programs. Finally, in the last step, we will explain the conclusion and future work, providing a complete summary of the whole project, the results obtained, and ideas for future improvements to enhance the project's performance.

II. METHODOLOGY

This section describes in detail the methodology used to identify driver behavior detection.

A. *Data Collection*

We gathered data using two methods:

The first method involved collecting the data ourselves from various sources, including samples of individuals both wearing and not wearing seatbelts, totaling approximately 8,000 samples.

The second method involved downloading data from Kaggle, which included distraction data with 10 different classes, each class containing approximately 3,000 samples. Additionally, we downloaded drowsiness data with 4 different classes, each class containing about 4,500 samples. All of this data has been labeled for use in our project.

B. *frame extraction*

To increase the amount of data and enable real-time processing for our model's predictions, we perform frame extraction on the video data by converting it into a series of images. This allows our model to analyze each image individually and make predictions based on the extracted frames.

III. RELATED WORK

A multitude of research studies have investigated the creation of driver monitoring and detection systems using various techniques. Some of these studies have aimed to detect fatigued and intoxicated drivers by gauging the driver's condition or analyzing the behavior of the vehicle.

Some researchers have aimed to detect the driver's age and level of intoxication, while others have focused on identifying the three primary types of distraction: manual, visual, and cognitive.

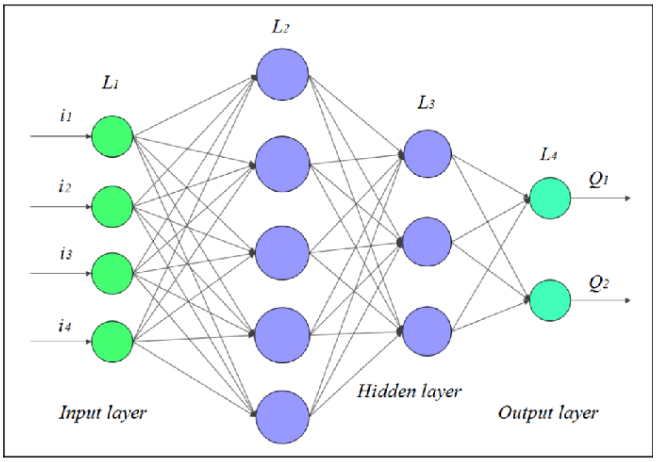
Other researchers have suggested a system to detect driver drowsiness.

A. *Abbreviations and Acronyms*

DL	Deep Learning
NN	Neural Network
CNN	Convolutional Neural Network
FC	Fully Connected
FC-CNN	Fully Convolutional Convolutional Neural Network
VGG	Visual Geometry Group

B. *Equations*

This network here is called Fully Connected Network (FNN) or Dense Network since every neuron has a connection with the node of the previous layer output. The Feedforward Neural Network or Sequential Neural Network is another term used to refer to it.



The equation for the neural network is a linear combination of the independent variables and their respective weights and bias (or the intercept) term for each neuron. The neural network equation looks like this:

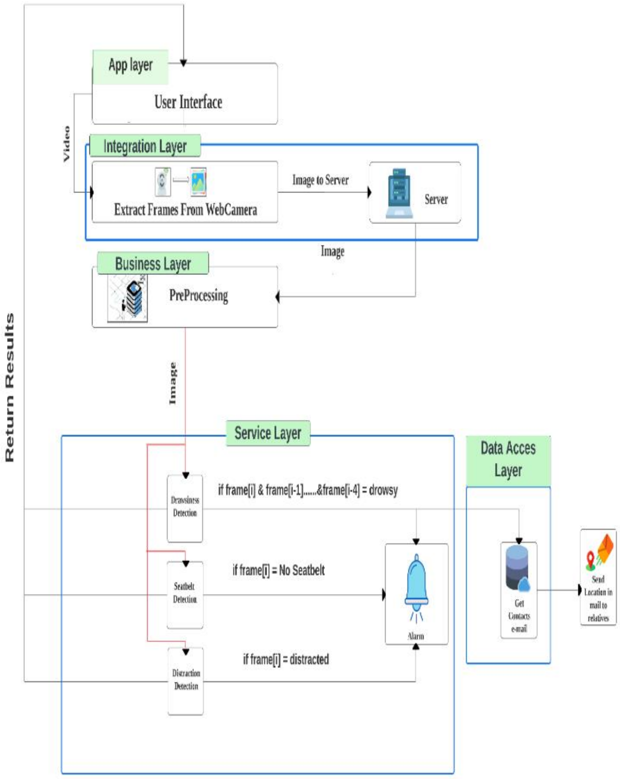
$$Z = Bias + W1X1 + W2X2 + \ldots + WnXn \qquad (1)$$

where,

- Z is the symbol for denotation of the above graphical representation of ANN.
- Wis, are the weights or the beta coefficients
- Xis, are the independent variables or the inputs, and
- Bias or intercept = W0

IV. SYSTEM ARCHITECTURE

This section provides a detailed overview of the system architecture for Driver Behavior Detection, which is illustrated in the accompanying Figure. The Driver Behavior Detection system is comprised of four distinct modules, including: (i) the Presentation Layer, (ii) the Business Layer, (iii) the Data Access Layer, and (iv) the mobile application.



A. *Application Layer*

The application layer in a system architecture with a user interface is responsible for managing the presentation layer and providing services to support user interaction, including data validation, input processing, and output rendering.

B. *Integration Layer*

This layer is responsible for managing the integration of different system components, including APIs, web services, and middleware.

C. *Business Layer*

This layer is responsible for managing the business rules and logic of the system, including data validation, business process management, and business intelligence.

D. *Service Layer*

responsible for providing reusable services that can be used by other layers of the system, including data access, messaging, and security services.

E. *Data Access Layer*

This layer is responsible for managing the data storage and retrieval of the system, including databases, file systems, and other data stores.

V. ROUTE RECOGNITION RESULTS

We conducted numerous experiments to validate the effectiveness of the algorithm and the Driver Behavior Detection system. Our results demonstrate that the system can operate successfully on a standard smartphone and achieve a lower computational cost compared to other similar methods.

Initially, we will present the results of the Drowsiness model in the provided figure. Subsequently, we will shift our focus to the Seatbelt model, followed by the Distraction model.

feature	Pre-Trained Model	Training Accuracy	Testing Accuracy	Training images	Testing images	Epochs	LR
Seat belt	Vgg16	99%	95.5%	7017 image 439 (Batch) 352 (batch for train) 87 (batch for validation)	1600 Image 100 (batch)	2	0.001
	Vgg19	99.4%	85.5%			5	
	MobileNet	98%	93%			5	
	ResNet 50	98%	83%			3	

Table 1. Detection accuracy rates of Drowsiness Model

feature	Pre-Trained Model	Training Accuracy	Testing Accuracy	Training images	Testing images	epochs	LR
Drowsiness	Vgg16	97.03%	88.66%	18012 Image 1126 (batch)	4600 Image 288 (batch)	8	0.001
	Vgg19	70.34%	60.55%			5	
	MobileNet	99.37%	96.63%			3	
	MobileNet V2	99.64%	93.75%			3	

Table 2. Detection accuracy rates of Seat belt Model

feature	Pre-Trained Model	Training Accuracy	Testing Accuracy	Training images	Testing images	epochs	LR
Distraction	Vgg16	98.7%	97.5%	30K	7K	2	0.0001
	Vgg19	96.5%	93%				0.001

Table 3. Detection accuracy rates of Distraction Model.

A. *Result of Drowsiness Model*

In table 1. displays the results of the Drowsiness model using several different architectures. Firstly, we utilized Vgg16 and achieved a training accuracy of 97.03%, with a testing accuracy of 88.66% after 8 epochs and a learning rate of 0.001. Secondly, we used Vgg19 and obtained a training accuracy of 70.34%, with a testing accuracy of 60.55% after 5 epochs and a learning rate of 0.001. Thirdly, we employed MobileNet and achieved a training accuracy of 99.37%, with a testing accuracy of 96.63% after 5 epochs and a learning rate of 0.001. Finally, we used MobileNet V2 and achieved a training accuracy of 99.64%, with a testing accuracy of 93.75% after 3 epochs and a learning rate of 0.001. This model was trained on 6548 images in the training dataset, with a batch size of 330, and on 2800 images in the testing dataset, with a batch size of 140.

B. *Result of Seat belt Model*

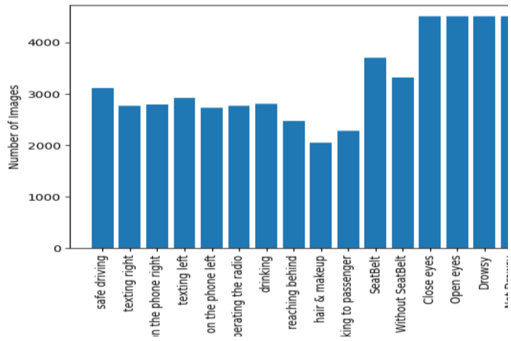
In table 2. displays the results of the Seat belt model using several different architectures. Firstly, we utilized Vgg16 and achieved a training accuracy of 99%, with a testing accuracy of 95.5% after 2 epochs and a learning rate of 0.001. Secondly, we used Vgg19 and obtained a training accuracy of 99.4%, with a testing accuracy of 85.5% after 2 epochs and a learning rate of 0.001. Thirdly, we employed MobileNet and achieved a training accuracy of 98.5%, with a testing accuracy of 93.5% after 2 epochs and a learning rate of 0.001. Finally, we used ResNet 50 and achieved a training accuracy of 98%, with a testing accuracy of 83% after 2 epochs and a learning rate of 0.001. This model was trained on 7017 images in the training dataset, with a batch size of 439, and on 1600 images in the testing dataset, with a batch size of 100.

C. *Result of Distraction Model*

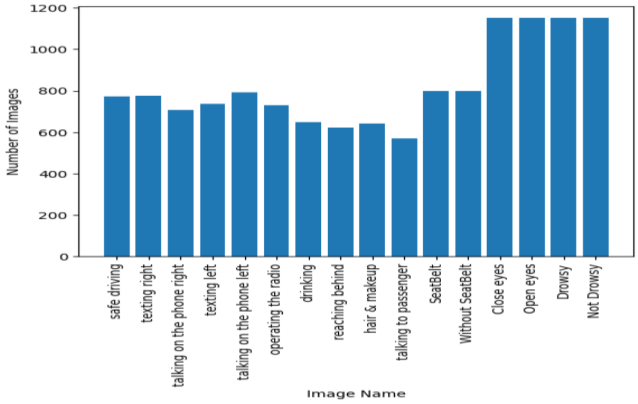
In table 3. displays the results of the Seat belt model using several different architectures. Firstly, we utilized Vgg16 and achieved a training accuracy of 98.7%, with a testing accuracy of 97.5% after 2 epochs and a learning rate of 0.0001. Secondly, we used Vgg19 and obtained a training accuracy of 96.5%, with a testing accuracy of 93% after 2 epochs and a learning rate of 0.001. This model was trained on 30000 images in the training dataset and on 7000 images in the testing dataset.

VI. VISUALISATION

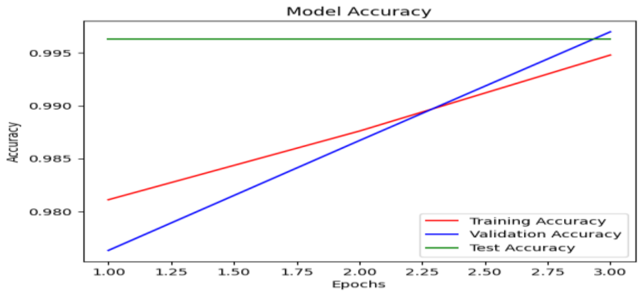
Initially, we present a visualization that displays the number of datasets for each class in the training set.



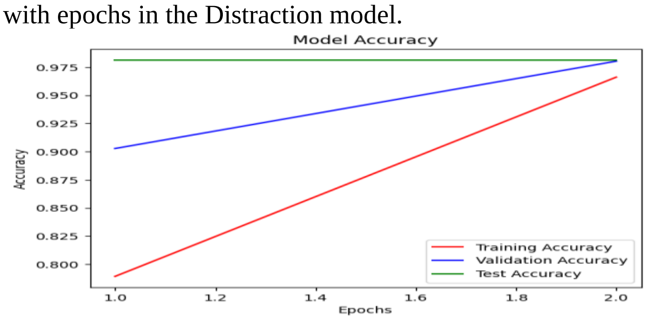
Next, we showcase a visualization that presents the number of datasets for each class in the testing set.



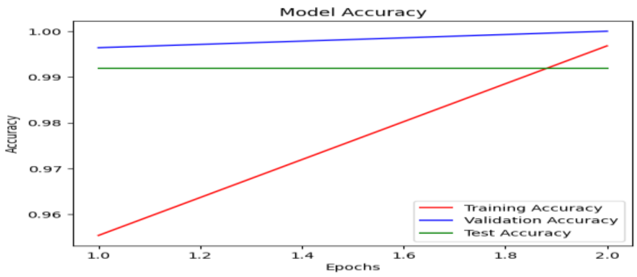
After that, we visualize the relationship between the training, testing, and validation sets with epochs in the Drowsy model.



Subsequently, we present a visualization that showcases the relationship between the training, testing, and validation sets with epochs in the Distraction model.



Lastly, we display a visualization that exhibits the relationship between the training, testing, and validation sets with epochs in the Seatbelt model.



VII. CONCLUSION

This paper presents a straightforward, yet effective approach based on CNN to identify various driving styles such as distraction styles, drowsiness styles, and seatbelt usage. The proposed method involves three primary stages: data gathering, pre-processing, and decision-making. First in data gathering we collect data from various sources like Kaggle website , roboflow website and we make also self-collected images in real time to increase volume of data after collecting data we split data into train, validation to make our models learn more enough and there is a part of dataset that the model has not ever seen to test the model and ensures that the model can predict model's classes well. The second step after collecting data is to make preprocessing on dataset after deliver it to the model so we made preprocessing on dataset such as we make resize for images and we made labeling for our dataset by two methods manually by hand and automated by the code after this phase we made also feature extraction from dataset to extract high features from our dataset to be as a input for our models. The third step and also the final step is decision making in this step we train our models to our dataset to be able to predict driver distraction and driver drowsiness and also if the driver wear the seatbelt or not. We have three models to predict the three features separately, model to predict if the driver wear the seatbelt or not and model for detect the style of driver distraction such as talking on the phone, drinking during drive his car, talking to the passenger, operating to the radio, texting someone, plays on his or her hair and make a make-up, reaching behind or safe driving and not make any style of distraction that we are talk about. And the final model about driver drowsiness this model can predict if the driver not drowsy or drowsy by detect if he or she sleep or yawning and can detect the driver eyes if his or her eyes open or close to ensure that he or she drowsy or not drowsy. And we have an application is called driver behavior detection the application takes real time images of the driver and detect firstly if he wears the seatbelt or not then detect if the same image has any style of distraction or not and finally the application take sequence of images to detect if the driver drowsy or not. There is a feature in our application that make a warning of the driver by making alarm if the driver is distracted or not wearing the seatbelt and if the driver is drowsy the alarm will turn on if the driver not walk-up the application will send email to his relatives to help him if he is in trouble.

ACKNOWLEDGMENT

The writer expresses deep appreciation and gratitude towards the doctors and TAs at Ain-Shams University for their dedication and guidance throughout the academic journey. Dr. Nermin Naguib and T.A. Muhammed Essam are specifically thanked for their invaluable support in a particular project. The writer also acknowledges the efforts of other doctors and TAs who have supported them throughout their academic journey, and thanks them for their passion for teaching and commitment to excellence. Finally, the writer thanks all the doctors and TAs for their unwavering dedication to education.

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