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Enhanced Generalization Performance in Deep Learning for Monitoring Driver Distraction: A Systematic Review

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ABSTRACT

Automatic analysis of driver behaviour is one of the most difficult subjects in the field of intelligent transportation systems. This study focuses on disturbed driver stance identification as part of the human action recognition methodology. Distracted drivers have been blamed for several vehicle crashes. Several research projects attacked the issue using various ways, including the use of invasive detectors, which are not practicable for mass production. The majority of the research done in the early 2010s relied on typical Machine Learning algorithms to complete the identification function. Many studies have been performed since the development of DL techniques to accomplish attention identification utilizing Neural Networks. Additionally, most of the study in the field has been done in a simulator or lab context, and the suggested system has not been validated in an actual situation. Most crucially, the field's study activities could be further separated into numerous sections. Many training methods, model properties, & feature choice parameters have been evaluated in this work, which seeks to give a comprehensive evaluation of machine learning methodologies employed for identifying driving distractions.

1. Introduction

Yearly, hazardous &dangerous driving behaviour kills over a million people and injures 50 million others worldwide. According to the NHTSA, distracted driving accidents died 3477 people & seriously wounded 391,000 people in 2015 [1]. A common cause of reported car accidents was texting or chatting on the phone while driving. The NHTSA defines distracted driving as "any action that diverts concentration from driving." Eating, drinking, talking to passengers, texting, talking on the phone, adjusting the stereo, drowsy driving, navigation system, or entertainment are all examples of distracted driving [2-4].The Centres for Prevention and Control of Diseases provides a more detailed

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description of distracted driving, classifying it into three categories: manual, visual, &cognitive. Several governments & automobile makers have made reducing car accidents caused by DD& improving roadway security by utilizing smart automobiles equipped with distracted driver's attitude sensors a top goal [5]. Furthermore, to improve road safety, police officers or radar cameras must be equipped with such distracted driving detectors to penalize the lawbreaker.

An issue was anticipated to worsen when more wireless or mobile devices are integrated into automobiles [6]. Although several European countries have restricted the use of smartphones, for example, while driving in recent years, it should not be expected that the level of driving distraction will eventually reduce [7,8]. Even in the absence of mobile device distraction, the usage of so-called in-vehicle information systems, such as navigation systems, could provide a further cause of potential distraction [9].One strategy, used by many cars manufacturers & automobile providers, aims to reduce the danger of accidents rather than distraction by developing dedicated supporting systems [10].

Machine learning (ML) and data mining (DM) methods could be capable to offer the appropriate methods to address such a difficulty [11]. ML was a method for searching vast amounts of information for previously unknown patterns. It was used effectively in business, health care, and other fields [12].This technology could be used to create a discriminating framework that captures the changes in behaviour when people drive regularly and when they are distracted [13]. The primary purpose of this study is to offer a nonintrusive technique for a real-time system to identify and categorize driver distraction using the ML method & solely vehicle dynamic information as model inputs [14]. Especially, they focus on the driver's visual distraction, which has been identified as a key factor in the analyses manoeuvres [15]. In this context, glancing away for a brief period could be regarded as a visual distraction from the driver's primary function.

Current challenges in monitoring driver distraction include limited accuracy of existing detection methods, difficulty in distinguishing specific distraction types, reliance on intrusive measures, and issues with real-time identification. Additionally, the integration of advanced technologies faces obstacles, such as high costs and potential privacy concerns. Standardization and effectiveness evaluation are ongoing challenges. Governments and auto manufacturers target road safety improvements through smart technologies like distracted driver's attitude sensors. Despite efforts, the integration of more wireless devices in vehicles poses an ongoing risk. Machine learning (ML) emerges as a potential solution, offering a nonintrusive real-time system for driver distraction identification. The proposed study focuses on using ML to categorize distractions, particularly emphasizing visual distraction, contributing to enhanced road safety through advanced technological intervention.

The research focus is on developing a nonintrusive real-time system utilizing machine learning methods to identify and categorize driver distraction, with a specific emphasis on visual distraction. The goal is to create a discriminating framework that captures changes in behaviour during distraction, using solely vehicle dynamic information as model inputs. The study aims to contribute to improved road safety by addressing the prevalent issue of distracted driving through advanced technological solutions.

2. Distraction Definition

Is it appropriate, as earlier questioned, to precisely identify &recognize the driver's state so that a system can provide as much assistance as the driver requires? The intervention of a forward-collision prevention system, for example, could be activated based on the driver's state [16]. If the concentration is identified, the function strategy could be modified correspondingly. On the other hand, if the system determines that the driver is not distracted but plans to overtake, the warning could be postponed or suppressed, even if a car ahead is nearing [17]. Such intelligent help, which recognizes the driver's intention & state, could allow for a wider safety margin while not annoying the driver with false alarms or unsuitable interventions in typical driving situations, thus improving user acceptance [18]. Several approaches to evaluating driver distraction or focusing on identifying and modelling fatigue or stress as primary causes of driver inattention have been published in recent years.

2.1 Driver Distraction

Driving an automobile is a very difficult endeavour. For many years, road safety professionals and other stakeholders have been concerned about concentration and, more broadly, driver inattention, as both significantly increase the chance of an accident [19]. For this reason, transportation and mobility researchers have been working hard on these problems for several decades [20]. Several scholars have proposed definitions for the term attention. DD, for example, is defined as 'the diversion of attention away from activities for secure driving and towards a competing activity.' Distraction happens when a driver's verification of data required to safely complete the driving job is delayed due to some event, activity, object, or individual within or outside the automobile that compels or induces the driver's shifting focus away from the driving task [21].

Although the fact that attention is a driver's cognitive state, studies distinguish various distraction identification methodologies, including optical distraction, manual distraction, & cognitive distraction. Drivers' attention is gradually shifting from their driving duty to non-driving associated secondary tasks by taking their hands, eyes, & minds off the road [22,23]. However, activities might include a combination of two, or even three, forms of distractions, increasing the danger of an accident. Auditory and voice distractions are two further types of driving distractions [24]. Cognitive distraction was perhaps the most challenging sort of attention to evaluating because it is challenging to witness what a driver's brain is doing. While verbal distractions have been described in the scientific literature, they weren't found to be substantially connected with accident liability [25-28].Several studies on driver inattention & distraction have been undertaken by various researchers.

Automated driving necessitates a handover between the driver and the automation system, and this takeover duty poses a major vulnerability in the automation system, as situation awareness is diminished and communication breakdowns could happen [29]. It is therefore critical to keep drivers "in the loop," for example, by providing continuous feedback on system limits or vehicle automation behaviour to issue discrete warnings, to increase the frequency of proactive reactions to automation mistakes, and enhance system understanding [30]. An 'in the loop' driver has physical control of the vehicle or monitors the driving situation, whereas an 'out of the loop' driver does not have physical control of the vehicle and does not inevitably monitor the driving circumstance, or has physical control of the automobile but does not monitor the driving circumstance [31]. Decreasing overtaking times for drivers performing non-driving operations was an assignment for human-machine interface developers [32].

They suggest a technique categorization for DD study based on our evaluation of the scientific literature (see Figure 1). As a result, they highlight two types of methodologies: techniques for distraction research in a laboratory setting and techniques for distraction monitoring that could be utilized both in a laboratory and on public roads [33]. After the experimental setting, drivers in the first category of methods are especially distracted in different scenarios, or their eyes are focused while the level of distraction is determined in the laboratory environment using an automobile simulator equipped with additional sensors [34]. The second class, on the other hand, is focused on in-vehicle cabin driver assessment to recognize specific sources of distraction [35]. Several approaches have been established to evaluate the degree of driver distraction induced by non-driving connected secondary activity [36]. Four of these are detailed in greater detail below. First, the box task technique seeks to quantify the cognitive burden produced by different distracting activities. Researchers could be carried out in the following ways: Participants can manipulate the size & position of a box on a screen by using pedals and the steering wheel [37]. Some restrictions vary their size and shape around this box. The participant's primary goal was to keep the regulated box within bounds [38]. The system records various intersections of the box with the borders and the standard variation of box size and position of the ideal size & position to evaluate a researcher's effectiveness.

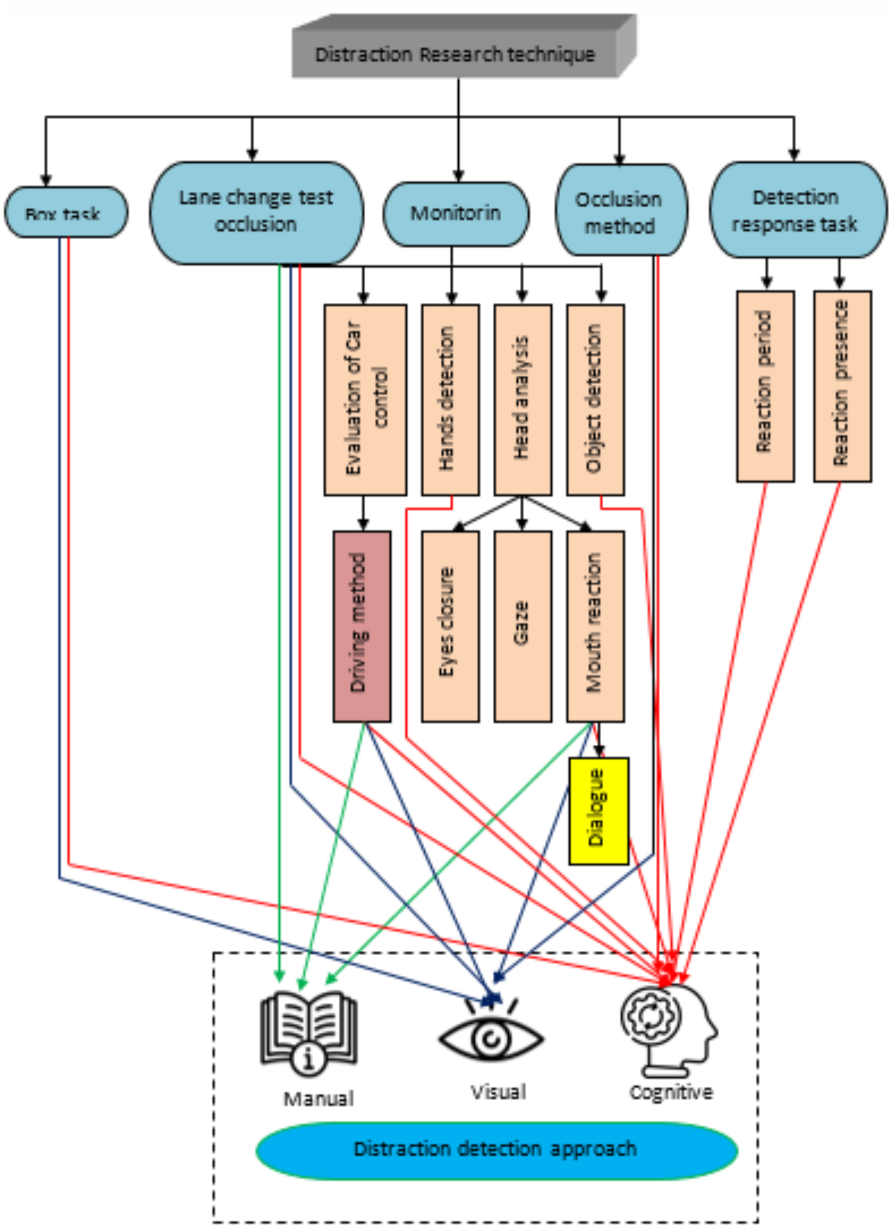

Fig. 1. Technique categorization for studies on driver distraction

Our literature research provides a complete technique architecture that analyses several driver monitoring approaches capable of assuming three categories of distraction, manual, visual, & cognitive distraction [39]. The schema was depicted in Figure 2. The ''Collected information'' column includes components that reflect raw, unprocessed sensor information. The nodes in the ‘‘Computed information’’ column indicate measurable observations calculated with observed data [40]. The ''Metrics & events'' column contains nodes that indicate factors that may be scientifically confirmed to directly indicate driver distraction. The column ''Inferred behaviour'' holds assumptions about a real-world situation that could be evaluated based on received facts. The ''Distraction type'' column lists the three kinds of DDs that the driver distraction detection system can identify. An internal camera, for instance, generates a video/depth map, which was used to determine gaze direction, identify events if the eyes were off the road & identify e.g. a phone, infers manual behaviour, e.g. texting, and therefore detect manual & visual distraction [41,42].

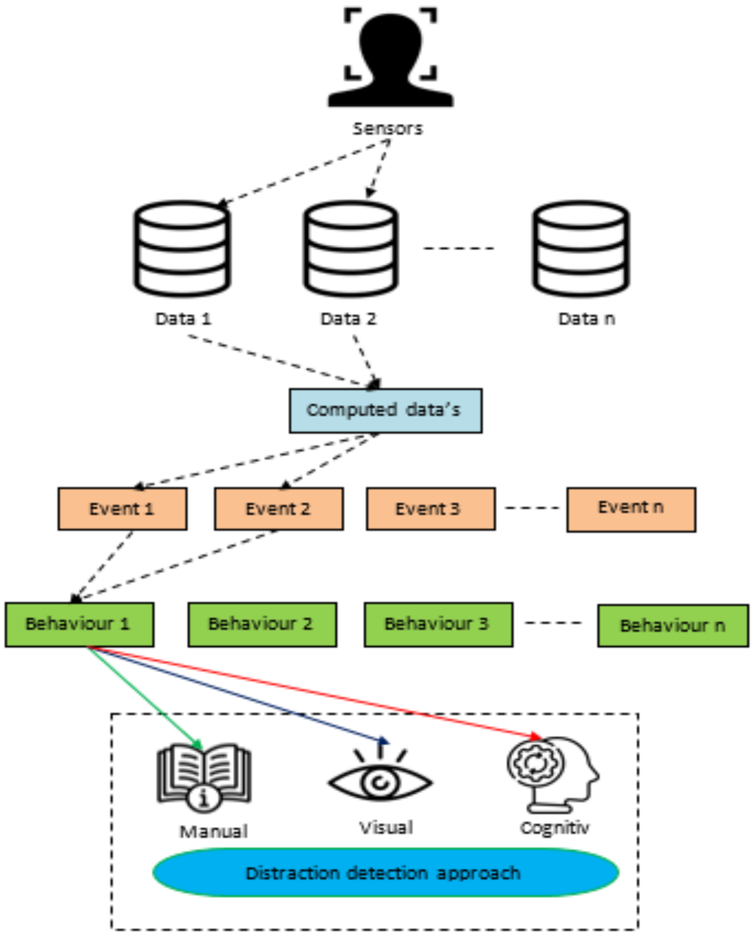

Fig. 2. The distraction detection technology

2.2 Deep Learning Background

DL has recently dominated visual comprehension tasks and demonstrated excellent results. The (CNN) deep learning method has made tremendous progress on image identification tasks [43]. Finding the ideal CNN architecture remains a challenging task. As a result, numerous architectures have been proposed in the past, including VGGNet, GoogLeNet, AlexNet, as well as most recently, the deep residual network [44]. The recurrent neural network, on the other hand, is a well-known technique that achieves outstanding results on time series challenges as well as language tasks such as speech detection & machine translation.

Artificial neural networks (ANNs), or commonly NNs, were information processing systems inspired by the HNSs and comprised of a large number of greatly interrelated processing pieces that collaborate to solve specific issues [45]. Signals are sent through connection links in a NN, which are defined by a related weight that is increased by the incoming signal in any normal neural net. Squeezing the net input into an activated function yields the output signal of a unit [46]. The FFNNs are one of the most essential forms of NNs employed in this paper. FFNNs have a structured framework, with every level consisting of units accepting input from units directly below them and delivering output directly above them [47]. There are no links between units within the same stage. FFNNs are classified as static networks because they lack feedback features & latency; the output is determined immediately from the input via feedforward connections [48].

In addition to static NNs, dynamic NNs have outputs that are dependent not just on the present input to the network but also on the network's earlier inputs, outputs, or states. Elman introduced LRNNs in a reduced form, and they are a type of dynamic network [49]. Recurrent networks are ANNs that apply to time-series information and use network unit outputs at time t as input to other units at time t + 1. According to this point of view, they promote a type of controlled cycle in the network [50]. Except for the last level, the LRNNs have a feedback loop with a single delay that wraps around every level of the network.

3. ResNet Model

Microsoft researchers created the ResNet model in 2016. In the ImageNet Large Scale Visual Recognition Challenge, the model obtained a state-of-the-art result of 96.4%. The network is quite deep, with 152 levels [51]. Additionally, the ResNet model provided unique residual blocks that leverage identity skips connections to address learning a very DL method. The residual blocks' function was to copy and execute the inputs of one layer to the next. The identity skips connection step solves the vanishing gradient problem by ensuring that the next level trains on something other than the input that the layer is comfortable with [52]. In addition to its accomplishment in the ILSVRC, ResNet has demonstrated outstanding outcomes on a variety of computer vision tasks.

Recent data indicate that network depth is critical for feature representation and generalization. It is typical to discover that just stacking convolutional layers to enhance method depth does not result in improved training and generalization accuracy. Residual Networks are a revolutionary deep CNN model that enables the building of higher convolutional neural networks [53]. ResNet won the ILSVRC 2015 categorization competition & the ImageNet detection, ImageNet localization, COCO detection 2015, and COCO separation by introducing the residual learning strategy.

The underlying mapping operator for the basic residual block could be considered to be H(x), as demonstrated in the left section of Figure 3. The x indicates the first-level inputs. The residual network assumes the existence of an intentional residual mapping function F(x) such that F(x)=H(x)-x, while the initial mapping was represented as F(x)+x. The primary idea underlying the residual network block is that, while both H(x) and the F(x)+x mapping could approach the desired functions asymptotically, the F(x)+x mapping was considerably easier to learn. Identification mapping is the addition of levels using the shortcut connection [54]. The right graph in Figure 3 depicts the entire framework of a DRN, with residual learning conducted every few stacked layers [55]. The DRNcan easily tackle the model degradation issue as the models go deeper by introducing identity mapping & copying the other layers from the shallower model.

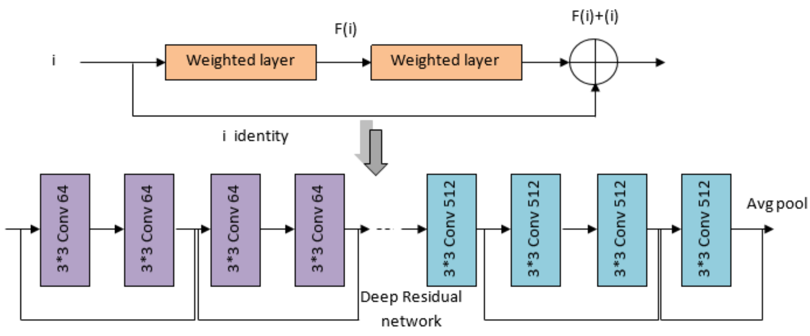

Fig. 3. Residual learning block and a deep residual network

3.1 GoogleNet

The GoogleNet framework is a deep CNN network proposed by Google researchers in 2014, which scored top-5 accuracy of 93.3% in the ILSVRC. The GoogleNet framework was complex, with 22 levels. The GoogleNet framework was built around a revolutionary building block known as the Inception framework. Instead of the traditional sequential procedure, this architecture employs a network at the network level [56]. Parallel computing was utilized in the design to calculate a large convolutional layer, a small convolutional layer, or a pooling layer. To minimize the dimension of the characteristics, the framework executes a one-by-one convolution procedure. Since the dimensionality reduction employed in this design and the parallelism that has been added, the number of variables & operations was greatly decreased; thus, these characteristics save memory &minimize computing cost [57].

Another deep CNN model that won the ILSVRC14 was GoogleNet. GoogleNet was substantially deeper than AlexNet, and its categorization outcomes on the ImageNet dataset were more precise. Regardless of model depth, GoogleNet's key innovation was the use of the Inception framework [58].As demonstrated, one of the most typical strategies for enhancing CNN model accuracy is to increase network size. However, it necessitates a big-scale database or a greater computing overhead. The Inception levels were included in the CNN model to boost layer sparsity and decrease the number of variables [59]. Each Inception level is made up of six basic convolution filters and one maximum pooling filter. With different scales, the parallel-arranged convolutional filters will have more accurate detailing and a broader representation of the information from previous layers [60]. Figure 4 depicts an ordinary dimension reduction Inception stage. The GoogleNet has two standard convolutional layers at the bottom level & nine Inception layers combined at higher levels [61]. The general number of variables in GoogleNet is 12 times fewer than that in AlexNet when Inception levels are used. Each Inception level contains six convolution filers and one max-pooling filter

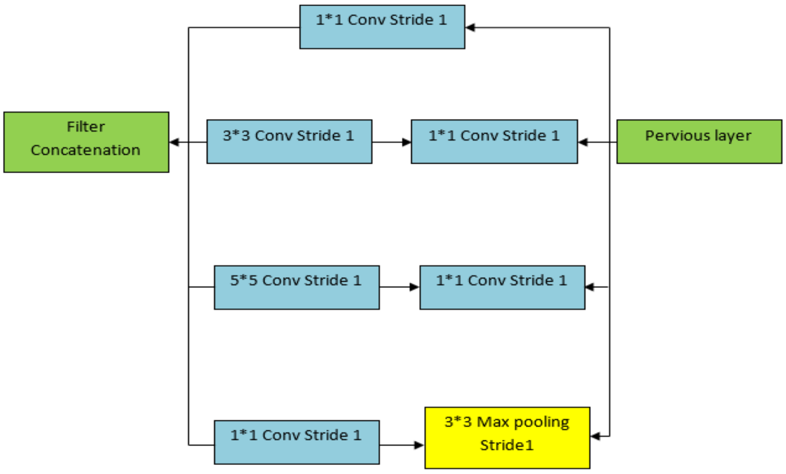

Fig. 4. The GoogleNet inception stage

3.2 Alexnet

DCNN has made remarkable progress in the field of computer vision. One of the most important explanations is the spread of the ImageNet database [62]. ImageNet is a massive database including over 15 million high-resolution annotated natural photos from over 22,000 classifications. The training of deeper and more precise CNN models benefits from a large number of tagged pictures [63]. Three DCNN models, AlexNet, GoogLeNet, & ResNet50, are chosen as the basic model structures for recognizing driver behaviour in this work. The ImageNet Large Scale Visual Recognition Challenge was won by AlexNet. The model was trained on 1000 classes from the ImageNet database. There are five convolutional layers & 3 fully linked neural network levels, including non-linearity & pooling layers between the convolutional layers. AlexNet has 60 million variables & 650,000 neurons [64].

4. Transfer Learning

Transfer learning is crucial in addressing challenges related to monitoring driver distraction. By leveraging pre-trained models on large datasets, it allows the adaptation of knowledge from one domain to another, enhancing the efficiency of distracted driving detection. This is particularly valuable in scenarios with limited labelled data, as transfer learning facilitates improved model performance, generalization, and accuracy in identifying diverse distracted driving behaviours. Importantly, it aids in overcoming data scarcity issues, making it an essential tool in developing robust and effective machine learning models for real-time driver distraction monitoring.

To train DCNNs like AlexNet, GoogLeNet, &ResNet from scratch, a large-scale annotated dataset like ImageNet was required. Large-scale tagged databases are always accessible for certain purposes. To develop DCNNs like AlexNet, GoogLeNet, &ResNet from scratch, a large-scale annotated database like ImageNet is needed. Large-scale tagged databases, on the other hand, are not always accessible for certain purposes. Because the original models were programmed to identify 1000 categories, the last few layers must be changed to satisfy the seven items or the binary categorization goal [65,66].The initial last fully linked layer and output level, which produce the probability for the 1000 groups, are replaced with a new fully linked layer, or Softmax layer, that produces the likelihoods for the seven classes.

The main structure & attributes of convolutional layers are preserved for these layers to retain their benefits in feature extraction & interpretation. Meanwhile, the knowledge gained from the large-scale ImageNet dataset could be applied to the area of driver behaviour. To slow down the update pace of the convolutional layers, a low starting learning rate is chosen. On the contrary, a considerably higher learning rate is selected for the final entirely linked layer to accelerate learning in the final layers. The convolutional layers in our work are not frozen because we discovered that completely freezing the convolutional layers reduces effectiveness [67]. As a result, a low updating rate was selected to let the convolutional layer adapt to the new categorization task. The new models may be educated to solve the new classification challenges using this combination.

4.1 Multiscale Recurrent Neural Network

Researchers from the University of Montreal proposed the hierarchical multiscale recurrent neural network in 2017. HM-RNN learns the hierarchical multiscale structure using temporal information. Instead of assigning predetermined update times, the framework automatically designs sufficient update rates that are comparable to the levels of abstraction layers. The researchers recommend using a binary detector at each layer for coarse and fine timeframes. The framework learns coarse timeframes for high-level layers & fine timeframes for low-level levels [68]. The boundary detector is activated when the section of the associated abstraction level is completely performed. Otherwise, the boundary sensor is turned off during segment execution. The researchers presented three methods that make use of hierarchical boundary states. Each time step can have one of these procedures. The UPDATE operation differs from the long short-term memory update rule in that it is processed sparsely based on observed boundaries [69].

4.2 Image Pre-Processing and Segmentation

In the realm of driver distraction, studies have employed Gaussian Mixture Models (GMMs) for effective feature representation and classification. Researchers have leveraged GMMs to model diverse distracted driving behaviours, showcasing their utility in accurately detecting and categorizing instances of distraction based on various driving-related features.

The method is used to segment the photos & remove the body region of the driver from the background. GMM was a method for unsupervised ML that could be used for data grouping and mining. It is a likelihood density function with a weighted sum of sub-Gaussian elements [70]. The primary benefit of utilizing GMM for unsupervised segment pictures is that it does not require manual labelling and can be easily modified by modifying the cluster centres. An image is represented by a characteristic vector based on pixel intensity to train a GMM-based segmentation algorithm [71]. The GMM's characteristic vector is a three-dimensional vector containing the RGB intensity of each pixel.

The segmented pictures of the 10 drivers for model training and testing are shown in Figure 5. The GMM classification approach [72] can identify the driver's head and body region. Since the camera is positioned inside the car, the driver's seat and related head position will be set in a specific area. The driver body region could be calculated using a predefined set of points situated around the driver's head position [73]. The driver areas should be indicated by the points surrounding the head position and the associated label. In the future, an automatic identification approach could replace the manual selection method [74]. For example, using head detection methods, a precise driver head position could be obtained, and then the driver body regions can be identified directly or via a basic semantic segmentation network [75]. As demonstrated in the following section, the segmentation-based strategy can significantly improve model identification accuracy.

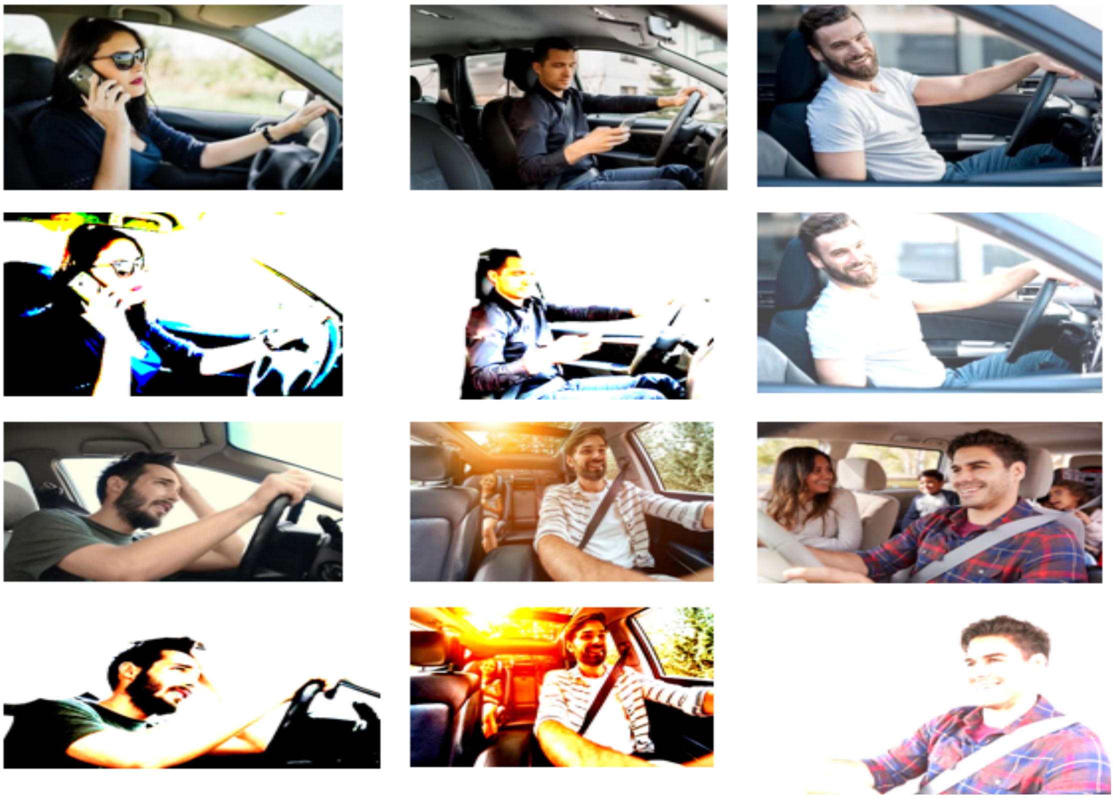

Fig. 5. Representation of the raw and segmented photographs

Table 1 analyses pertinent research from the literature. It should be noted that making an accurate cross-platform comparison of existing studies is challenging due to differences in methodology [76].

Table 1
Feature extraction classification results

ID	Method	Validation	Platform	Subjects
[24]	FFNN & Random Forest	Loo, Recognition: 83.4%	Real vehicle	6 drivers
[47]	Sequential model with AdaBoost & HMM	Loo, Recognition: 85.2%, Detection: 89.9%	Simulator	9 drivers
[48]	CNN+RNN sequential feature extractor with SVM classifier	Cross Validation 91% in average	Simulator	4 drivers
[19]	SVM, RUSBoost, KNN	Loo, recognition rates of different task are among 66%-86%	Real vehicle	21 drivers
[49]	Transfer learning with AlexNet & Inception V3	CV, 76% training data & 26% testing, 95.7% in average	Real vehicle	32 drivers
[50]	Transfer learning with VGG16, AlexNet, GoogleNet & ResNet	Loo, recognition accuracy in the range of 87% & 93%	Simulator	11 drivers

5. Conclusion

The article provides a review of the scientific literature on distracted driving. DD techniques that had been reviewed were combined into a comprehensive driver distraction architecture to detect the three primary types of distraction: manual distraction, visual distraction, & cognitive distraction.

The suggested framework describes the complete distraction detection process, from sensor data collecting to data processing, behaviour inference, and distraction-type assessment. As a result, this article serves as a primer for all scholars interested in both driver distraction research and driver distraction detection systems, making the material useful for transportation system developers as well. According to the classification results, separation contributes to a far more precise identification result than the algorithm developed with raw photos. Further contrast is provided between transfer learning and other approaches to feature extraction.

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