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Driver Fatigue Monitoring System Using an Artificial Intelligence Algorithm Model

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Abstract

Road safety is seriously threatened by fatigued drivers. Many people's lives and well-being are at risk due to the disastrous effects of drowsy driving. The National Safety Council estimates that sleepy driving contributes to over 100,000 traffic accidents every year, which cause roughly 71,000 injuries and 1,550 fatalities. These figures highlight how urgently coordinated actions are needed to address this serious road safety issue and save lives. In this paper, we focus on finding ways to detect and monitor driver drowsiness and fatigue, and how these factors increase the likelihood of serious accidents and tragic loss of life. We present a model for working as training a convolutional neural network. To detect driver fatigue and drowsiness, data from the Kaggle website must be examined to develop a sophisticated and up-to-date system. We have conducted a thorough review to ensure the accuracy of the models, assessments, and procedures.

Keywords: Deep learning, Driver fatigue, Max-pooling, Dataset preparation, and Multilayer network.

1. Introduction

Over the years, car accidents have been a serious source of loss of life, in addition to the resulting material losses. The causes of these accidents are numerous and varied, most of which are related to drowsiness and fatigue, but unfortunately, they often lead to fatalities. Naturally, there are no effective treatments to reduce driver fatigue or drowsiness other than advising drivers to sleep, rest, and avoid driving for extended periods, advice which is often ignored. Therefore, this topic requires the development of methods to mitigate these issues (Abu *et al.*, 2022; Begum *et al.*, 2024).

Depending on the most recent statistics approximately 1.25 million people die annually worldwide due to traffic accidents from the World Health Organization, most of which are a result of

fatigue, lack of sleep, and not getting enough rest (Rajat *et al.*, 2017). Given the utmost importance and to save the largest possible number of drivers and citizens who may be traveling with the driver in the bus or car, solutions that rely at artificial intelligence algorithms, whether machine type of learning or deep type of learning, have emerged and are being employed in various ways (Zhao *et al.*, 2016). In order to prevent accidents and save lives, numerous studies have been carried out to determine whether a driver is too sleepy or exhausted to continue driving. In order to get results in this field, a group of researchers applied machine learning techniques. For instance, the Nearest Neighbor (KNN) algorithm, decision trees, and Support Vector Machines (SVM) classification techniques were employed to identify driver fatigue and eye con-

dition. In addition, face-eye pairs were identified using the Viola-Jones method. Using the PERCLOS approach, the driver's level of sleepiness was assessed by looking at whether their eyes were open or closed (Öztürk *et al.* 2022). While other research studies focused on deep learning for driver drowsiness detection systems, they also explored the development and application of drowsiness detection models employing convolutional neural network models (CNNs), sometimes enhanced with transfer learning, with the potential to improve training performance through data processing. Several CNN models have shown positive results, including the LenNet-5, AlexNet, VGG models, Convolutional Residual NN, and YoLo, all of which are types of deep-trained networks (Maya *et al.*, 2026; Zhao *et al.*, 2020; Mohammadiounotikandi and Babaeitarkami, 2024).

In conclusion, every study started by taking pictures or videos of the driver's face and examining their facial characteristics. As previously indicated, a camera installed on the dashboard takes these pictures. Monitoring the driver's eye condition and assessing the extent of eye opening is the first stage. A dataset of previously taken photos or videos can be used for this, and the dataset is trained to analyze the outcomes (Thabit *et al.*, 2025; Thabit *et al.*, 2024). Additionally, the degree of mouth opening is tracked since it helps the algorithms evaluate the photographs and gives information on the driver's yawning state. Since examining the image data exposes traits like exhaustion and drowsiness, the driver's activity level and facial condition are also covered (Punitha *et al.*, 2014; Sanjeeva *et al.*, 2023).

This study uses a classification system depending on deep type of learning to determine whether or not a driver is sleepy. The dataset, which included 2904 photos of a group of people, was created using Python. In order to get the best results while reviewing the dataset, a convolutional neural network was used in conjunction with a variety of Python tools and techniques, such as cleaning, feature selection, scaling, and data segmentation into four categories.

Related Work

The researchers also presented a driver drowsiness detection model using convolutional neural networks followed by an emotional state analysis,

i.e., an analysis of the mental state, thereby identifying the motivating factors for various driving styles, by introducing factors that directly affect driving, such as vehicle speed, engine revolutions, vehicle size and load, driving hours, driver facial recognition, and driving time, in order to analyze the driver's behavior and emotional and mental state (Chand *et al.*, 2021). While other researchers employed all types of convolutional neural networks, both old and new, comparing the results and determining which model was better in accuracy and performance for detecting driver drowsiness and fatigue, the researchers used several network layers and the fewest possible parameters to ensure the model performed with minimal system cost, effort, and time. This approach, known as "learn-to-learn," aimed to guarantee results with minimal system input (Venkateswarlu *et al.*, 2024). The research in this field doesn't end there. Another group of researchers focused their efforts on the eye area of the face only, considering that drowsiness and eye strain are the starting point, which is limited by whether the driver is tired, drowsy, or distracted. They also used a multi-layered convolutional neural network combined with Grand CAM technology to improve the accuracy of the captured images, which will be subjected to deep learning (Florez *et al.*, 2023).

Furthermore, the use of machine learning algorithms has expanded in this field to obtain results for detecting driver drowsiness. This includes all algorithms that can provide comprehensive studies and results in this area. The database consists of analytical tables of all the attributes that can be used for training and evaluation. It can also include images or videos, which are converted into a set of graphs before training and analysis begin (Essahraui *et al.*, 2025; Varma *et al.*, 2023; Deepika *et al.*, 2025). Specifically, during this decade, much research has focused on detecting driver drowsiness due to the rising number of traffic accidents due to recognize body movements as trained traits, thus driver fatigue and drowsiness. Many machine learning algorithms have been used to detect and analyze drivers' faces, with system improvements such as data cleaning, correcting missing values and unbalanced data tables, and other processing methods, in addition to data augmentation and mobile learning (Phulari *et al.* 2021; Prasath *et al.*, 2022; Cheerla *et al.*, 2022).

2. Methodology

The first step is data collection, where cameras are initially set up toward the front of the driver's side face to take pictures of him driving the car and record this on video so that we can study all the facial positions and situations. The first step is input, where cameras are positioned toward the front of the driver's side face to record images of them driving and record the footage. This allows for the analysis of all facial expressions and positions. The second step involves analyzing and studying the driver's facial features, which represent eye opening and closing, mouth case opening and closing, and yawning. These features are then used as input for deep learning. In the third step, these features are used to train the system, make decisions based on them, and classify the output. After a training period and ensuring the effectiveness of the training, a small portion of the data is analyzed without providing the output result, allowing the algorithm to enable the detection of the driver's drowsiness. In

this paper, the proposed system for detecting driver fatigue is implemented in stages, as shown in **Fig. 1**, explained flowchart that represent proposed system. Research papers have continued to present models for deep learning in the topic of driver drowsiness detection through the analysis of facial images captured by a dashboard-mounted camera. Initially, by employing machine learning and a deep type of learning, specifically neural networks, with especially convolutional neural networks, researchers presented a two-stage analysis of the acquired images as a database. The first stage involved detecting driver drowsiness through eye twitching, and the second stage consisted of technical procedures using artificial intelligence models, including neural networks that providing an intelligent impression of the driver's case of attention or alertness (Sharif *et al.*, 2019; Kshirsagar *et al.*, 2022).

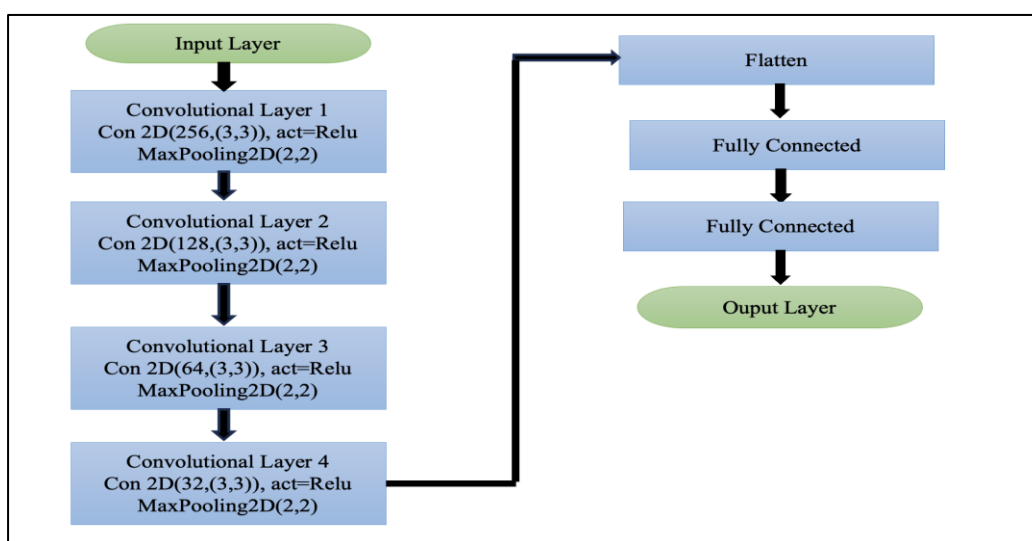


Fig. 1: Architecture Layers of CNN Model.

The proposed model includes several stages to reach the final results. These stages work sequentially to give the training algorithms the best results. It is important to obtain a suitable database on which deep learning can be performed. These images undergo pre-processing in terms of size. Image size must be standardized within an appropriate size, with filters applied at all stages. A suitable Max Pooling should be used with the report. If possible, stride with the padding can be used to prevent important information from being lost in the image due to the filtering process. These steps are called the Data Collection with data preparation and

adjustment phase, along with the deep learning tools preparation phase.

Data Augmentation

To improve model performance to the point where training and testing can be considered more effective in terms of the amount of data used, along with the correct choice of the algorithm employed, the size of the data used is just as important as the algorithm itself. Diverse and large datasets contribute to making the algorithm better; therefore, the algorithm performs better when the data is more varied, and vice versa. Thus, the principle of data increasing is a

crucial tool that treatment with deep learning processes. It relies on expanding existing datasets to create new data samples that enhance the model's creation capabilities and efficiency (Thabit *et al.*, 2025).

Description of Data

The dataset group used in this paper consists of four volumes of color images in four categories: 726 images that represent closed eyes, 726 images that represent open eyes, 725 images of people not in case yawning, finally, 723 images subgroup of people in case yawning, totaling 2900 images. The proposed methodology was implemented on a MacBook Air with a speed of 2.50 GHz and 8 GB of RAM, Ventura 13.6.1, using python software.

Proposed Model

This research paper presents a procedure for detecting driver drowsiness or fatigue by analyzing facial images captured by a dashboard-mounted camera. Initially, it relies on deep learning via a multi-layered convolutional neural network, which classifies the driver's case into four main categories

as the following: closed eyes, open eyes, yawning, and non-yawning. This classification allows for the detection of eye drowsiness or mouth yawning. The process utilizes an effective set of automated features provided by the convolutional neural network training method, enabling the highly accurate classification output of the driver's case as either drowsy, non-drowsy. It is generally accepted that artificial intelligence tools, which study the correlation and variation in underlying relationships within image data, acquire superior characteristics for representing raw data. The deep neural network structure adopted in this research is multi-layered and includes a triple filter (3,3) in each layer, as well as using the Max-Pooling in each layer with dimensions (2,2). The activation function in all internal layers is Relu function, and we used dropout ratio of 0.5 in the flatten layer. The following **Fig. 2** illustrate the overall construction of the remarkable neural network model and the details of the structure network in each layer.

```
model = Sequential()

model.add(Conv2D(256, (3, 3), activation="relu", input_shape=X_train.shape[1:]))
model.add(MaxPooling2D(2, 2))

model.add(Conv2D(128, (3, 3), activation="relu"))
model.add(MaxPooling2D(2, 2))

model.add(Conv2D(64, (3, 3), activation="relu"))
model.add(MaxPooling2D(2, 2))

model.add(Conv2D(32, (3, 3), activation="relu"))
model.add(MaxPooling2D(2, 2))

model.add(Flatten())
model.add(Dropout(0.5))

model.add(Dense(64, activation="relu"))
model.add(Dense(4, activation="softmax"))

model.compile(loss="categorical_crossentropy", metrics=["accuracy"], optimizer="adam")

model.summary()
```

Fig. 2: Proposed Model in Details.

3. Results and Discussion

Here, we present the experimental results obtained for the driver fatigue detection system. The experiments were conducted using Python 3 and the Anaconda environment, specifically the Jupiter application. The database was obtained from the

Kaggle website. The data were then processed as described above, where the model was trained on four data sets, each representing a class of images. The testing and training were carried out as shown in the **Fig. 3**, using several stages of convolutional neural network folding.

Model: "sequential"		
Layer (type)	Output Shape	Param#
conv2d (Conv2D)	(None, 143, 143, 256)	7168
max_pooling2d (MaxPooling2D)	(None, 71, 71, 256)	0
conv2d_1 (Conv2D)	(None, 69, 69, 128)	295040
max_pooling2d_1 (MaxPooling2D)	(None, 34, 34, 128)	0
conv2d_2 (Conv2D)	(None, 32, 32, 64)	73792
max_pooling2d_2 (MaxPooling2D)	(None, 16, 16, 64)	0
conv2d_3 (Conv2D)	(None, 14, 14, 32)	18464
max_pooling2d_3 (MaxPooling2D)	(None, 7, 7, 32)	0
flatten (Flatten)	(None, 1568)	0
dropout (Dropout)	(None, 1568)	0
dense (Dense)	(None, 64)	100416
dense_1 (Dense)	(None, 4)	260
Total params: 495,140		
Trainable params: 495,140		
Non-trainable params: 0		

Fig. 3: Folding Architecture Models with Parameters.

The training of the convolutional neural network shown in the table above was completed in several stages. Initially, a small number of trials (25) were performed, with the highest accuracy achieved being [94.5]. The number of trials was then doubled, and the highest value of accuracy achieved is [97.40]. Next, the number of trials was increased to (75), with the highest accuracy achieved being [97.28]. Finally, the number of trials is increased to (100), and the highest value of accuracy achieved is [97.40]. Thus, we concluded that there is no need to take a larger number of trials at the expense of time and system strain, as we still obtain the best result with 50 trials.

4. Conclusion

In this research paper, we utilize a deep type of learning training database depend on a multi-layered convolutional model of neural network. We conducted training in several stages to ensure satisfactory results in addressing the problem of driver drowsiness and fatigue, and the resulting loss of life and property. We are developing a deep learning framework that meticulously analyzes all observable variables and takes appropriate action to detect driver fatigue. We achieved approximately 98% accuracy in detecting driver drowsiness and fatigue, preventing potential accidents caused by it, making roads safer, and reducing traffic accidents resulting from drowsy driving. In the future, we will explore machine learning and deep type learning methods, including those that achieve performed without supervision or prior training. We will also explore

expanding the database to cover wider areas to differentiate and identify factors related to roads, weather conditions, or driving hours, as well as determining the percentages that can be exceeded using artificial intelligence models.

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6. Conflicts of Interest

There are no conflicts of interest in this paper.

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