2023 3rd International Conference on Smart Generation Computing, Communication and Networking (SMART GENCON)
Karnataka, India. Dec 29-31, 2023

2023 3rd International Conference on Smart Generation Computing, Communication and Networking (SMART GENCON) | 979-8-3503-1912-5/23/$31.00 ©2023 IEEE | DOI: 10.1109/SMARTGENCON60755.2023.10442238

A Convolutional Neural Network-Based Method for Real- Time Eye State Identification in Driver Drowsiness Detection

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***Abstract*— The use of Convolutional Neural Networks (CNNs) for drowsiness detection is an AI-based method for detecting and warning of human drowsiness or weariness. Deep learning models like convolutional neural networks (CNNs) learn by analysing images or videos, often focusing on human faces or eyes. Drowsiness cues may be recognised by these models, including drooping eyelids, yawning, and altered facial expressions. CNN-based sleepiness detection may be used to generate alarms or cautions using economic resources in real-time applications, such as driver monitoring systems, to help avoid accidents and improve safety. Artificial intelligence and computer vision access are at the heart of this technology, which aims to alleviate major safety risks associated with sleepiness and exhaustion. In this research, drowsiness detection and classification are accomplished with the help of a Sequential Convolutional Neural Network (CNN) model. The graphics processing unit (GPU) is used for producing preliminary data processing. The Deep Learning model is then shown graphically by analysing the Loss and Accuracy curves. With a predicted accuracy of 96%, the suggested model would pave the way for more research into sleepiness detection and categorization.**

Keywords*— *Artificial Intelligence, Computer Vision, Image Processing, Deep Learning, Drowsiness Detection, Remote Sensing, Model Training, Classification*, *CNN, Sequential Model, Deep Learning

I. INTRODUCTION

The investigation of drowsiness detection in the field of artificial intelligence (AI) is a crucial and essential subject of research that has wide-ranging implications in several areas, such as driving safety, healthcare, and industrial environments. Academic researchers have been actively engaged in the development of novel methodologies for the detection of sleepiness via the use of artificial intelligence (AI) technology. The following are prevalent techniques and areas of investigation in the field of sleepiness detection:

- Eye-tracking and blink detection are two important techniques used in several fields of research and technology. These techniques include the analysis and measurement of eye movements and blinking patterns to gain insights into cognitive processes, human-computer interaction
- Numerous artificial intelligence (AI) systems prioritise the examination of eye-related characteristics in order to identify signs of tiredness. Factors such as blink rate, blink length, and ocular closure are monitored. Machine learning models, such as neural networks, have the capability to undergo training in order to identify patterns related to sleepiness by analysing eye behaviour.
- Computer vision methods are used by researchers to analyse facial expressions in order to detect indications of tiredness, such the presence of drooping eyelids, yawning, or alterations in facial muscle activity.
- Facial signals may be recognised via the use of deep learning models such as Convolutional Neural Networks (CNNs).
- The identification of alterations in head posture, such as nodding or abrupt movements, may serve as an indication of tiredness.
- Artificial intelligence (AI) methods, such as pose estimation models and object tracking, have the capability to be used for the purpose of monitoring head motions.
- Physiological sensors are devices that are capable of measuring and monitoring various physiological parameters of the human body. These sensors play a crucial role
- Artificial intelligence (AI) has the potential to be combined with physiological sensors such as EEG (Electroencephalography), ECG, and EMG (Electromyography) in order to observe and track brain function, heart rate, and muscle activity.
- Machine learning models have the capability to analyse sensor data in order to identify patterns indicative of tiredness.
- Audio-based artificial intelligence (AI) systems has the capability to analyse several aspects of speech, including speech patterns, fluctuations in voice tone,

and even the presence of snoring noises, in order to identify signs of tiredness. For this goal, the use of deep learning models or audio signal processing methods is feasible.

- The concept of multimodal fusion refers to the integration of many modes of information or data in order to enhance understanding or decision-making processes.
- The integration of data from several sources, including eye-tracking, face analysis, and physiological sensors, has the potential to improve the precision of sleepiness detection.
- Academic researchers are now investigating methodologies for integrating and combining data from many sources.
- Real-time monitoring refers to the continuous and instantaneous observation and tracking of a system or process.
- Numerous sleepiness detection systems using artificial intelligence have been developed with a primary focus on real-time monitoring, particularly in domains such as driver assistance systems.

Deep learning approaches such as Recurrent Neural Networks (RNNs), Long Short-Term Memory (LSTM) networks, and hybrid models are extensively used in the field of sleepiness detection for the study of time-series data. The creation of accurate and well-annotated datasets for the purpose of training and evaluating sleepiness detection systems is a crucial component of artificial intelligence (AI) research in this domain. Academic researchers often gather data from many sources and meticulously label it in order to construct training datasets. The collaboration between psychologists and human factors specialists in interdisciplinary research aids AI researchers in gaining a more comprehensive understanding of the physiological and behavioural manifestations associated with tiredness.

When considering the deployment of a system or technology, there are many important factors that need to be taken into account. These considerations include factors like as privacy, user acceptability, and real-world limits are being considered by researchers as they investigate feasible deployment techniques for sleepiness detection systems. Researchers are now investigating feasible implementation options for sleepiness detection systems, taking into account many variables such as privacy concerns, user acceptability, and real-world limitations.

The area of drowsiness detection in artificial intelligence (AI) research is characterised by its dynamic nature, as it undergoes constant development and refinement. Researchers are always striving to enhance the precision, resilience, and versatility of drowsiness detection systems, ensuring their effectiveness in many domains. The primary objective of researchers is to create systems that possess the capability to consistently identify sleepiness, hence improving safety and overall welfare in diverse settings.

II. LITERATURE

Jahan et al. provided a comprehensive explanation on the development of a drowsiness detection system that uses eye state prediction to assess a driver's level of tiredness. This system aims to proactively inform the driver of potential hazards to road safety before they escalate into catastrophic incidents [1]. In their study, Florez et al. (year) introduced a methodology for the identification of sleepiness in drivers, with a specific emphasis on analysing the eye area. This choice is motivated by the fact that ocular tiredness is often seen as an initial indicator of drowsiness [2]. The objective of Lee et al. was to develop a deep neural network that could be used for the identification of sleepiness based on electroencephalography (EEG) signals across several states of consciousness, including wakefulness, sleep, and drowsiness [3]. Dinesh et al. developed a prototype method for detecting tiredness. The system operates by monitoring the visual focus of drivers and emitting a warning signal in the event that they get drowsy while operating the vehicle [4]. According to Hussein, R.M. et. al, it was determined that the presence of sleepiness and tiredness has a detrimental effect on driving performance, leading to increased vulnerability of drivers to hazardous circumstances [5]. In a study conducted by Yogarajan et al., it was shown that the system had the capability to accurately identify sleepiness, hence establishing its reliability and efficiency as a valuable tool for enhancing road safety. The suggested method aims to mitigate the occurrence of accidents resulting from sleepy driving, hence enhancing overall road safety for all motorists [6]. In their study, Adhithyaa, N. et al. proposed a novel multistage adaptive three-dimensional convolutional neural network (3D-CNN) model that incorporates many expressive characteristics for the purpose of detecting driver drowsiness (DDD). The researchers specifically focused on addressing the issues of system complexity and performance in their approach [7-8]. In their study, Li et al. introduced a compact convolutional neural network (CNN) for the purpose of quantifying eye closure. This CNN was designed to analyse eye pictures obtained via a wearable glass prototype. Notably, the prototype was equipped with a hot mirror-based design, enabling the camera to be conveniently mounted on the temples of the glasses [9-10]. Ahmed, M.I.B. and colleagues have suggested a model that presents a methodology for assessing the degree of driver weariness by analysing alterations in a driver's eye movement via the use of a convolutional neural network (CNN) [11-12]. Thite, S.S. et. al conducted a comprehensive analysis with the objective of gaining a thorough understanding of the strengths, limits, and prospective avenues for enhancing sleepiness detection systems. This was achieved by an exploration of several research papers and advancements in the area [13-14]. In their study, Alajlan, N.N. et al. provided a comprehensive examination of TinyML. Following the completion of early trials, a proposal was put out for the use of five lightweight deep learning models that are suitable for deployment on a microcontroller [15-16]. Almazroi et al. introduced an innovative methodology for detecting driver fatigue by analysing eye and mouth movements, as well as identifying distracting objects during the operation of a motor vehicle [17]. The authors, Vijaypriya, V. et. al, proposed a framework known as MCNN (Multi-Scale Convolutional Neural Network) for the purpose of classifying sleepiness [18-19]. The authors, Alameen, S.A. et. al, put out a spatiotemporal model aimed at detecting visual signs of tiredness in films. The proposed framework relies on the integration of a three-dimensional convolutional neural network (3D-CNN) and long short-term memory (LSTM) architecture. The 3DCNN-LSTM model is capable of analysing lengthy sequences by using the 3D-CNN technique to extract spatiotemporal information from neighbouring frames [20].

The sentences that follow give a condensed overview of the study's key results.

The major purpose of this study is to classify and predict different types of sleepiness seen in pictures. The technique relies on a fine-tuning approach applied to a sequential CNN model.

The criteria assessed in this study have the potential to be of assistance to researchers who have struggled to build an effective organisational framework.

Improvement strategies and their impact on outcomes are among the many topics covered.

Multiple subtopics make up the research. The article's third part describes the dataset that was analysed, while the fourth describes the method that was employed to preprocess the data. The definition and training of a sequential convolutional neural network (CNN) model consists of five distinct procedures. Results are presented in Section 6, and a full list of citations may be found at the conclusion of the presentation in Section 7.

III. INPUT DATASET

The photos in the dataset were obtained from Kaggle as an open source dataset. The dataset comprises a collection of photographs depicting an individual engaged in the act of operating a motor vehicle. The provided picture has been used for the purpose of evaluating the performance of a trained model in detecting signs of tiredness inside an image. The visual representation consists of an individual exhibiting a yawn while occupying the driver's position inside an automobile. A total of 4000 photos are present, which have been classified into four categories: closed eye, open eye, no yawning, and yawning, as seen in Fig. 1.

(a) (b)

(c) (d)

Fig. 1. Dataset image of (a) Closed eye (b) Open Eye (c) No yawn (d) Yawn

IV. DATA PRE-PROCESSING

The process of data preparation is of utmost importance in the domain of identifying visual data related to Drowsiness. The use of suitable preprocessing methodologies ensures that the data is adequately processed and prepared for the specific objective of training a machine learning model. Upon the completion of these preparatory procedures, the dataset comprising of proposed photos has been appropriately processed and is now ready for use in training a machine learning model, which may be employed for the purpose of classification.

V. DEFINING AND TRAINING OF SEQUENTIAL CNN MODEL FOR DROWSINESS IMAGE CLASSIFICATION

The process of developing and training a Sequential Convolutional Neural Network (CNN) model for the purpose of classifying drowsiness images encompasses several essential stages. These stages encompass the formulation of a neural network structure, preprocessing of the dataset, and the careful selection and implementation of suitable methodologies and parameters for model training.

```
Model: "sequential"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
conv2d (Conv2D)              (None, 78, 78, 256)       7168
_________________________________________________________________
max_pooling2d (MaxPooling2D) (None, 39, 39, 256)       0
_________________________________________________________________
conv2d_1 (Conv2D)            (None, 37, 37, 128)       295040
_________________________________________________________________
max_pooling2d_1 (MaxPooling2 (None, 18, 18, 128)       0
_________________________________________________________________
conv2d_2 (Conv2D)            (None, 16, 16, 64)        73792
_________________________________________________________________
max_pooling2d_2 (MaxPooling2 (None, 8, 8, 64)          0
_________________________________________________________________
conv2d_3 (Conv2D)            (None, 6, 6, 32)          18464
_________________________________________________________________
max_pooling2d_3 (MaxPooling2 (None, 3, 3, 32)          0
_________________________________________________________________
flatten (Flatten)            (None, 288)               0
_________________________________________________________________
dropout (Dropout)            (None, 288)               0
_________________________________________________________________
dense (Dense)                (None, 64)                18496
_________________________________________________________________
dense_1 (Dense)              (None, 4)                 260
=================================================================
Total params: 413,220
Trainable params: 413,220
Non-trainable params: 0
_________________________________________________________________
```

Fig. 2. Layer-wise architecture of proposed sequential Model

The distinctive characteristic of the sequential convolutional neural network (CNN) model is in its specific architectural arrangement, whereby the layers are structured in a sequential fashion, with each subsequent layer following the preceding one in a linear sequence. Sequential models are a basic kind of neural network design that exhibits robust performance in tasks that include data conforming to a linear or sequential pattern. These approaches are often used in many applications like as image recognition or the study of sequential data, including time series or textual content. This research paper presents a novel Sequential model that facilitates the sequential stacking of layers, as seen in Fig. 2, with the aim of enhancing the training process of a model particularly designed for Drowsiness Image Classification and identification.

VI. RESULTS

A. Drowsiness Image Classification Using Sequential CNN Model

The process of categorising drowsiness pictures using a Sequential Convolutional Neural Network (CNN) model entails the development of a neural network structure and its subsequent training to accurately classify aspects related to drowsiness based on the provided data categories.

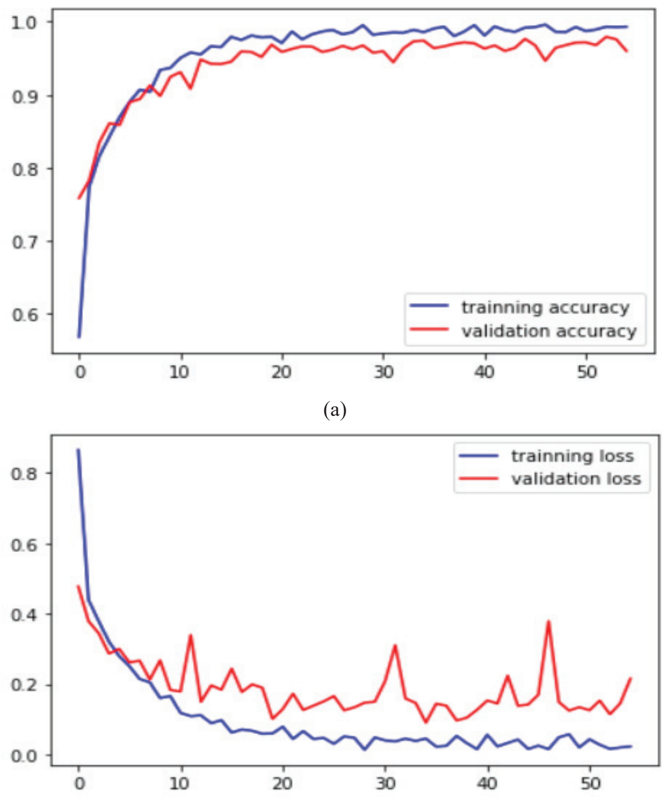
TABLE I. EPOCHS CALCULATION DEPICTION ON SEQUENTIAL CNN MODEL

Epoch	Training Loss	Training Accuracy	Validation Loss	Validation Accuracy
1	0.8645	0.5687	0.4773	0.7586
5	0.2796	0.8695	0.3001	0.8586
10	0.1664	0.9367	0.1837	0.9245
15	0.0979	0.9651	0.1844	0.9421
20	0.0602	0.9793	0.1015	0.9686
25	0.0475	0.9866	0.1511	0.9586
30	0.0489	0.9819	0.1501	0.9576
35	0.0458	0.9858	0.0908	0.9741
40	0.0155	0.9953	0.1274	0.9703
45	0.0163	0.9918	0.1423	0.9766
50	0.0204	0.9927	0.1348	0.9714
55	0.0234	0.9931	0.2158	0.9600

A sequential model is a kind of deep learning architecture that is characterised by a linear arrangement of layers. The Sequential API in Keras, a deep learning framework, is used for the construction of models that conform to a pre-established sequence. The layers are arranged in a sequential manner, which promotes a systematic flow of information from the first layer to the last one. Various approaches are used to ascertain the ideal number of epochs for training a Sequential Convolutional Neural Network (CNN) model. The model's performance is continuously watched, while concurrently ensuring that it does not excessively adapt to the training data. The aforementioned information may be found in Table I.

B. The training and validation curves of the exploratory data analysis (EDA) conducted using the proposed sequential model.

By graphing the variations in accuracy and loss over the training procedure, valuable insights may be gained on the gradual improvement of the model. If there is an increase in the accuracy of the training data, but the accuracy of the validation data stays same or decreases, it suggests that the model is too focused on the training data and performs poorly when faced with new or unfamiliar data. The convergence of the accuracy and loss curves suggests that the suggested model has achieved successful learning. If there are frequent and substantial oscillations in the curves, it may be imperative to adjust the hyperparameters. Learning rate annealing is a technique that involves gradually adjusting the learning rate throughout the course of training. It is important to consider that the curves shown in Fig. 3 are intended to enhance understanding of the training process's operation. These sources may assist the presentation of significant information about the determination of the ideal stoppage point of training, prospective modifications to the learning rate, and the viability of adopting tactics such as dropout or batch normalisation.



(a)

(b)

Fig. 3. Training and Validation (a) Accuracy (b) Loss on visualized curves

VII. CONCLUSION

The use of Convolutional Neural Networks (CNNs) for the purpose of detecting drowsiness has been extensively employed in academic research spanning several fields. CNN-based sleepiness detection systems have a significant impact on improving safety, health, and the comprehension of human behaviour and cognition within research applications. These systems use the capabilities of deep learning and computer vision to autonomously detect and react to indications of tiredness inside real-life scenarios. The present study utilises a Sequential Convolutional Neural Network (CNN) model to achieve the detection and categorization of sleepiness. The graphics processing unit (GPU) is used for initial data processing. The graphical representation of the Deep Learning model is then shown via the analysis of the Loss and Accuracy curves. The proposed model, which is anticipated to achieve an accuracy rate of 96%, has the potential to facilitate further investigation into the identification and classification of sleepiness.

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