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Distracted Vehicle Driving Detection Using Artificial Intelligence by Identifying Potential Distractions and Alerting for the Same

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Abstract: This project explores the integration of artificial intelligence (AI) techniques to augment driver detection systems in automotive environments, aiming to enhance overall road safety. The proposed system leverages advanced computer vision algorithms and machine learning models to accurately identify and monitor drivers in real-time. Key aspects include facial recognition, gaze tracking, and behavioural analysis to assess driver attentiveness and emotional states. The AI-assisted driver detection system contributes to proactive safety measures by providing timely alerts for potential driver distraction, fatigue, or impairment, detects weather the driver is drowsy, and also if the driver is continuously distracted even after limited number of alerts, our system will notify drivers superior or relative about repeated mistakes as a part of security. The project involves the development and evaluation of a prototype using diverse datasets and simulation scenarios to validate the system's effectiveness in various driving conditions. The outcomes offer valuable insights into the potential of AI in mitigating road accidents and improving overall transportation safety.

Keywords: Artificial Intelligence, Machine Learning, driver distraction detection, Computer Vision, facial recognition, gaze tracking, behavioural analysis.

I. INTRODUCTION

In recent years, the rising concern for road safety has led to the development of advanced technologies aimed at mitigating the risks associated with distracted driving. Among these innovations, the integration of Artificial Intelligence (AI) into distracted driver detection systems stands out as a transformative approach to enhancing safety on our roads. This introduction provides an overview of the AI-assisted distracted driver detection system, highlighting its significance, core features, and potential impact on preventing accidents caused by driver inattention [1]. This project explores the integration of artificial intelligence (AI) techniques to augment driver detection systems in automotive environments, aiming to enhance overall road safety.

The proposed system leverages advanced computer vision algorithms and machine learning models to accurately identify and monitor drivers in real-time. Key aspects include facial recognition, gaze tracking, and behavioral analysis to assess driver attentiveness and emotional states. The AI-assisted driver detection system contributes to proactive safety measures by providing timely alerts for potential driver distraction, fatigue, or impairment, detects weather the driver is drowsy, and also if the driver is continuously distracted even after limited number of alerts, our system will notify drivers superior or relative about repeated mistakes as a part of security [2]. The project involves the development and evaluation of a prototype using diverse datasets and simulation scenarios to validate the system's effectiveness in various driving conditions.

The outcomes offer valuable insights into the potential of AI in mitigating road accidents and improving overall transportation safety. This groundbreaking project focuses on harnessing the power of artificial intelligence (AI) to revolutionize driver detection systems within automotive environments, with the primary objective of significantly improving road safety. By seamlessly integrating cutting-edge AI techniques, our system aims to go beyond conventional approaches, employing advanced computer vision algorithms and state-of-the-art machine learning models[3].

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II. RELATED WORK

The proposed framework employs a knowledge-distillation-based approach to address the issue of high parameter count in Convolutional Neural Networks (CNNs) for distracted driver recognition. A high-performance teacher network is constructed using progressive learning, enhancing robustness to illumination changes from shallow to deep layers of a CNN[4]. Dataset used in this approach are State farm Distracted Driver Detection Dataset, AUC Distracted Driver Dataset, Drive &Act Dataset (for spatial-temporal 3D convolutional neural network extension).Accuracy obtained in this approach are as follows : Teacher Network Accuracy on AUCD3: 96.35%, Student Network Accuracy on AUCD3: 95.64% with only 0.42M parameters , Teacher and Student Network Accuracy on SFD3: 99.86%–99.91%, 3D Student Network Accuracy on Drive &Act Dataset: Outperforms previous state-of-the-art by a significantly large margin, 0.89%–29.00% higher in the validation set, and 2.05%–30.88% higher in the test set [5].

The paper proposes a Convolutional Neural Network (CNN) named mobileVGG for detecting and classifying driver distraction. The architecture is based on depth wise separable convolutions to achieve computational efficiency. Using this approach, they achieved 95.24% and 99.75% accuracy on the American University in Cairo (AUC) and Statefarm's distracted driver detection datasets, respectively. MobileVGG exhibits real-time performance crucial for Advanced Driver Assistance Systems, outperforming state-of-the-art CNN architectures in accuracy, speed, and model size, processing 108 fps on NVIDIA P100 GPU and 34 fps on an Intel Xeon Processor CPU, demonstrating practical applicability [6].

The paper suggests a practical method for detecting distracted and fatigued driving, striking a balance between performance, operational simplicity, and hardware feasibility. It judges whether the driver has distracted driving behavior with a support vector machine (SVM) classifier based on the information of head and eye movement. It detects the relative positions of face and hand with multiple scale faster region-based convolutional neural network (RCNN) in order to determine whether the driver is calling. Uses K-nearest neighbours to recognize the distinctions of different behaviours .

The paper introduces the "100-Driver" dataset with 470,000+ images, addressing limitations in existing datasets and providing a framework for practical distracted driver classification. PyTorch facilitates neural network construction and training, employing CNNs, image preprocessing, and feature extraction. The evaluation involves images from 4 cameras observing 100 drivers over 79 hours from 5 vehicles .

III. PROPOSED SYSTEM

The proposed system aims to leverage artificial intelligence (AI) techniques to detect instances of distracted driving in real-time. By analysing various cues, including driver behavior, vehicle dynamics, and environmental factors, the system will identify potential distractions and issue timely alerts to the driver to mitigate the risk of accidents [12].

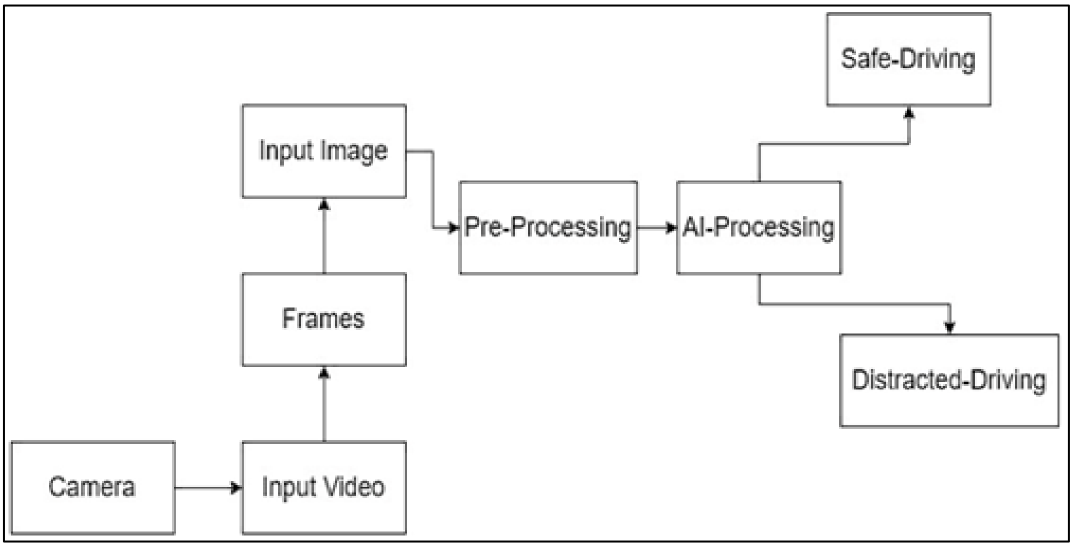

Fig. 1 Proposed Model for Prediction of Safe and Distracted Driving

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Based on the image, the proposed model contains the following main steps:

- Data Acquisition(Input Image/Input Video)
- Frames Generation (if the input is a video)
- Pre-Processing
- AI-Processing (using VGG-16 architecture)
- Safe-Driving (output prediction)
- Distracted-Driving (output prediction)

A. Data Acquisition

In this initial phase, the system gathers the requisite data to train and validate the AI model. This data encompasses images or videos capturing drivers engaged in various states of attentiveness while operating a vehicle.

Acquisition sources may include dashcam recordings, publicly available datasets, or specialized data collection setups. It's paramount to ensure diversity in data, considering factors like lighting conditions, driving environments, and driver demographics for a robust model[13] .

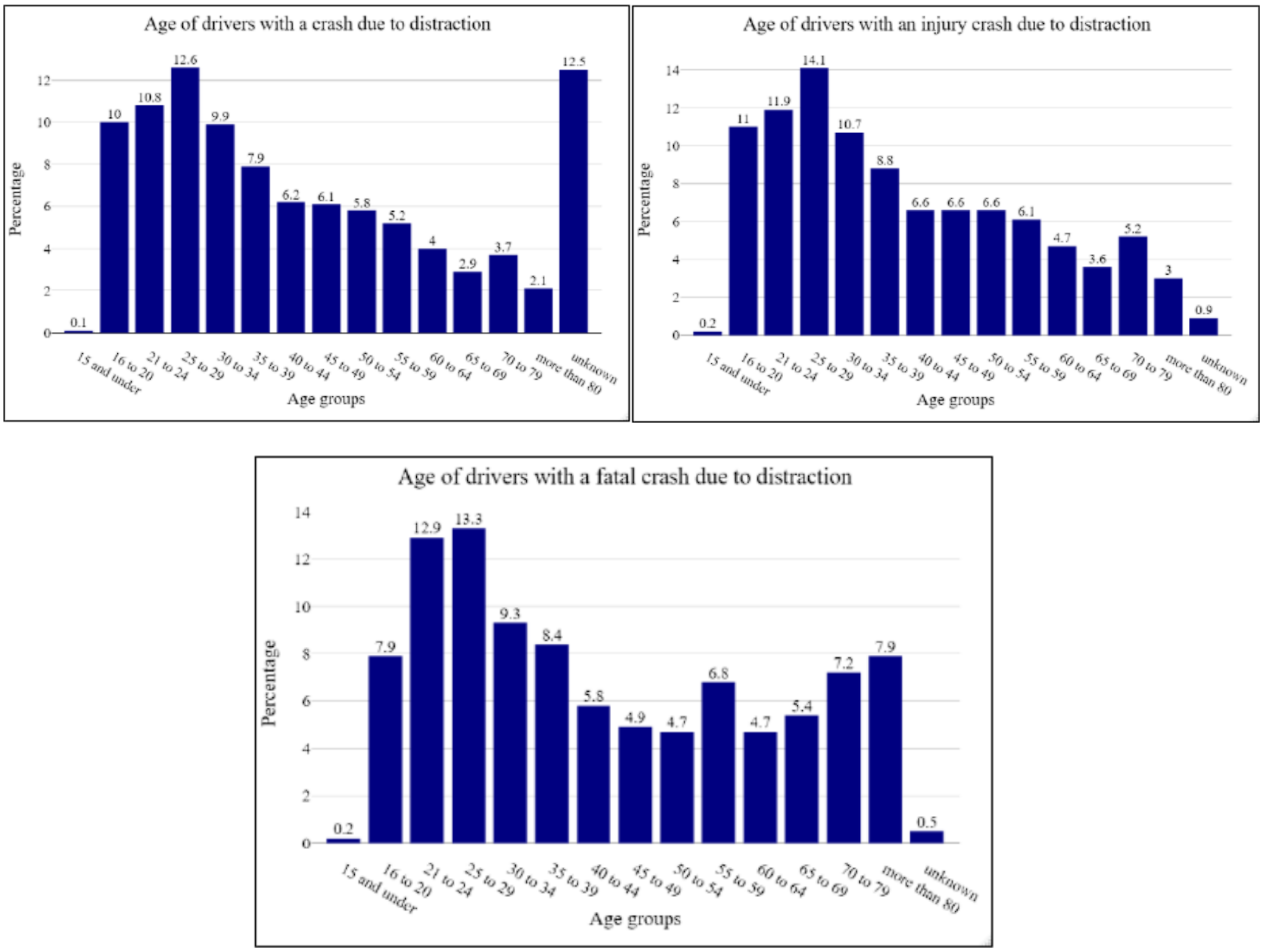

Figure 2: Socio-demographic Distribution

B. Frames Generation

When the input comprises video footage, the system undergoes a process of frame extraction. This entails breaking down the video content into individual frames, enabling the subsequent analysis of each frame independently [14]. Various video processing libraries or custom scripts can accomplish this task efficiently.

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i) Video Input:

The process begins with obtaining video input, typically captured by a dashboard camera or other recording devices installed within a vehicle. This footage contains continuous sequences of frames depicting the driver's actions and the surrounding environment.

ii) Frame Extraction:

Frame extraction entails dissecting the video input into individual frames, each representing a single snapshot of the scene at a particular moment in time. This step is crucial for subsequent analysis, as it allows the system to examine each frame independently for signs of distracted driving behavior.

iii) Frame Encoding and Storage:

Once extracted, each frame is typically encoded into a standard image format (e.g., JPEG, PNG) for efficient storage and processing. The encoded frames may be organized into a sequential order to maintain temporal continuity, facilitating subsequent analysis and interpretation.

iv) Quality Control:

Quality control measures may be implemented to ensure the fidelity and integrity of the extracted frames. This can involve checking for errors or artifacts introduced during the extraction process, such as frame skipping or distortion, and rectifying any anomalies to maintain data integrity.

v) Storage and Indexing:

Finally, the extracted frames, along with any associated metadata, are stored in a structured format conducive to efficient retrieval and analysis. Indexing mechanisms may be employed to facilitate rapid access to specific frames based on temporal or spatial criteria, streamlining subsequent processing tasks [17].

After the data acquisition, the dataset is pre-processed to improve the quality of data and features are extracted from the pre-processed input data. Information can be processed and extracted from images for machine interpretation.

C. Pre-Processing

The pixels in the image can be manipulated to any desired density and contrast and also images can be stored and retrieved easily through following steps :

i) Resizing:

Images or frames extracted from videos may come in varying sizes. Resizing involves adjusting all images to a standardized size to ensure uniformity in the input data. This is crucial for the neural network to process the data efficiently [18]. Typically, resizing is done while preserving the aspect ratio to avoid distortion.

ii) Normalization:

Normalization is the process of scaling pixel values within the images to a standard range. This ensures that the input data has a consistent distribution, which can help improve the convergence of the neural network during training. Common normalization techniques include scaling pixel values to a range between 0 and 1 or standardizing them to have a zero mean and unit variance.

iii) Noise Reduction:

Images or frames extracted from videos may contain noise or artifacts that could interfere with the neural network's ability to extract meaningful features. Noise reduction techniques, such as Gaussian blurring or median filtering, can be applied to smooth out irregularities and enhance the clarity of the input data. This can improve the robustness and accuracy of the model's predictions [19].

iv) Data Labelling (For Supervised Learning):

In supervised learning scenarios where the input data is labelled with corresponding ground truth labels (e.g., safe driving or distracted driving), pre-processing may also involve organizing the data into input-label pairs. This ensures that the neural network learns to associate specific input patterns with corresponding output predictions during training.

D. AI-Processing (using VGG-16 architecture)

The AI processing phase, utilizing the VGG-16 architecture along with a custom CNN (Convolutional Neural Network) implemented in a Jupyter Notebook named "Custom CNN Non-Batch.ipynb," is a critical component of the distracted driving detection system. Here's a detailed description of this phase [20].

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i) VGG-16 Architecture:
VGG-16 is a deep convolutional neural network architecture known for its simplicity and effectiveness in image recognition tasks. It consists of 16 layers, including convolutional layers, max-pooling layers, and fully connected layers. The convolutional layers extract hierarchical features from input images, while the fully connected layers perform classification based on these features.

ii) Custom CNN (Convolutional Neural Network):
In addition to VGG-16, the project incorporates a custom CNN implemented in the "Custom CNN Non Batch.ipynb" Jupyter Notebook [21]. This custom CNN is likely tailored to the specific requirements and nuances of the distracted driving detection task. It may have a different architecture, including varying numbers of layers, filters, and activation functions, optimized for the dataset and detection objectives.

iii) Input Data from Video Streams:
The input data for this phase is derived from video streams captured by dashboard cameras or similar devices installed in vehicles. Each video stream consists of a sequence of frames representing snapshots of the driving scenario at different time intervals.

iv) Pre-processing:
Before inputting the video frames into the AI models, pre-processing steps are applied to prepare the data. This includes tasks such as resizing the frames to a standardized resolution, normalizing pixel values, and potentially augmenting the data with transformations to increase its diversity and robustness.

v) Feature Extraction:
The VGG-16 architecture and the custom CNN are utilized to extract features from the pre-processed video frames. Each model analyzes the frames to identify relevant patterns and features indicative of distracted driving behavior. The hierarchical nature of convolutional neural networks allows them to capture both low-level and high-level features, such as edges, textures, and object shapes [22].

vi) Model Training:
If the project involves supervised learning, the AI models, including VGG-16 and the custom CNN, are trained using labeled data. During training, the models learn to associate specific features extracted from the video frames with corresponding labels indicating safe or distracted driving behavior. This process involves optimizing the model parameters through techniques like backpropagation and gradient descent.

vii) Inference and Prediction:
Once trained, the AI models are deployed to perform inference on new video streams. They analyze the frames in real-time or batch-wise to make predictions regarding the driver's behavior. These predictions classify each frame as either indicative of safe driving or distracted driving based on the learned patterns and features [23].

viii) Output and Visualization:
The output of the AI processing phase includes predictions generated by both the VGG-16 architecture and the custom CNN. These predictions are typically aggregated and analyzed to provide insights into the prevalence of distracted driving behavior over time, across different driving scenarios, or among different drivers. Visualization techniques such as charts, graphs, or heatmaps may be employed to present the results effectively.

By leveraging the capabilities of VGG-16 and a custom CNN, the AI processing phase plays a crucial role in identifying distracted driving behavior from video input data, contributing to the overall effectiveness of the detection system .

IV. CONCLUSION

In conclusion, our research has demonstrated the efficacy of artificial intelligence in detecting distracted driving behaviors, thereby contributing to the advancement of road safety initiatives. Through the development and evaluation of a robust AI-driven detection system, based on the VGG-16 architecture, we have shown results in identifying instances of texting, talking on the phone, and other distractions from onboard camera footage.

Our findings highlight the potential of leveraging machine learning algorithms to enhance driver monitoring capabilities and mitigate the risks associated with distracted driving.

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