Detecting Drowsy Through Eye Closure and Yawning : Azure Custom Vision System

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Abstract* — With growing concerns about road safety, the increasing number of accidents caused by driver drowsiness has become a major issue. This study addresses the detection of drowsy driving by employing deep learning techniques to recognize sleep states in drivers. Azure Custom Vision model is propounded to identify closed eyes in constant facial images of drivers. The proposed approach offers versatile applications such as human-computer interaction design, facial expression recognition, and fatigue detection in drivers. The AZURE Custom Vision utilizes the Convolutional Neural Network VGG16 model with Azure. A dataset is created by capturing the drowsy driving instances and are trained. Our model achieves a total detection accuracy of 99.3%, outperforming other existing algorithms in the field. For instance, RNN achieved an accuracy of 92%, while CNNs reported an accuracy of 96.51%. Compared to these models, our approach demonstrates superior accuracy, leveraging the deep hierarchical feature extraction capabilities of VGG16 to more effectively distinguish between drowsy and wakeful states.

Keywords -- Convolutional Neural Network, VGG16, driving, drowsiness, Image Classification, AZURE Custom Vision

I. INTRODUCTION

The rising number of road accidents continues to be a major public safety challenge [1]. Globally, approximately 1.25 million individuals lost their lives in road accidents last year, with India reporting concerning figures. The Ministry of Road Transport and Highways (MORTH) reported a staggering 1,68,491 fatalities in 2022, surpassing the previous year's count of 1,53,972 [2]. The myriad causes of these accidents are reckless driving, speeding, driving under the influence, human error, and notably, driver drowsiness [3]. Recognizing the seriousness of this issue, the researchers in this study aimed to mitigate road accidents by addressing driver fatigue, a significant risk factor in transportation systems [4]. Studies have established drowsiness as a leading cause or contributing factor in road accidents, equating driving while fatigued to driving under the influence of substances [5].

The real-time detection of drowsiness emerges as pivotal solution to curbing road accidents [6]. Research efforts have explored different methods, including experiments with sound stimuli to wake up drivers. Investigating the efficacy of signals at 3100 Hz and 450 Hz, the study found that 92% of individuals awoke from the latter, demonstrating its effectiveness [7]. Additionally, studies have examined the impact of car seat vibrations on driver alertness, with certain frequencies proving conducive to maintain wakefulness [8]. Through observation tests employed in driving simulators, the authors observed the heightened alertness in participants which is exposed to vibrations within specific frequency ranges [9].

Drowsiness detection systems can be broadly categorized into vehicle-oriented and driver-oriented monitoring systems [10]. While vehicle-oriented systems analyze driving behaviors via vehicle sensors to detect sleepiness, driver-oriented systems rely on facial features for drowsiness recognition [11]. The dynamic nature of the human face, especially the eyes, is crucial for identifying drowsiness. [12]. Another pertinent study explores enhancing vehicle intelligence and interactivity to alert users in critical situations. It emphasizes the prevalence of driver exhaustion from sleep disorders or deprivation [13]. Continuous driving without breaks has been correlated with increased drowsiness, underscoring the imperative of rest breaks to prevent accidents [14]. Various studies have employed descriptive tests, such as vehicle-focused, physiological, and behavioral measures, to assess driver drowsiness and discover methods to improve safety. [15]. These measures offer valuable insights into existing systems, highlighting challenges and areas for improvement in developing robust drowsiness detection systems [16].

To assess driver drowsiness, various methods like behavioral analyses and sensor-based metrics have been used. While these methods offer insights into existing systems, they also have limitations such as missing subtle signs of drowsiness or issues with accuracy. This study explores these methods and concludes that a hybrid detection system combining non-intrusive physiological measures with other metrics could effectively warn drowsy drivers and reduce road incidents.

Our proposed model aims to mitigate reported traffic accidents stemming from driver drowsiness, leveraging a pre-trained algorithm to streamline the process. In contrast to other methodologies, this study employs the AZURE Custom Vision utilized the Convolutional Neural Network (VGG16) algorithm for direct drowsy detection by localizing the eyes, complemented by the Custom vision Tag Tool for dataset annotation. The subsequent sections delve into the experimental methodology and findings of this study.

II. LITERATURE SURVEY

Younes Ed-Doughmi et al.,2020 examines a deep learning architecture using RNN and 3D ConvNets, trained on a large-scale video dataset, to detect and prevent driver drowsiness, achieving 97% accuracy. While effective, our solution requires a more customized dataset and cannot predict drowsiness without posture change. Future work could incorporate physiological data to address this limitation [17].

Shikha Pachouly et al., 2020 examines the Drowsiness detection was achieved by identifying facial features using CNNs to classify eye states and examining yawning frequency with OpenCV and Dlib in Python. An alarm alerts the driver upon detecting drowsiness. Limitations include detection challenges in varying lighting conditions, obstructions, and wearing sunglasses [18].

Khubab Ahmad et al., 2023 examines drowsiness detection systems are crucial for road safety, with AI advancements enhancing their performance. Vehicle-based systems offer strong performance and ease of use, while behavior-based, physiological-based, and hybrid systems face challenges such as privacy concerns, user inconvenience, and limited datasets. Addressing these challenges can improve the effectiveness and accessibility of drowsiness detection applications [19].

Rohith Chinthalachervu et al., 2022 examines a drowsiness detection system using machine learning algorithms and visual behavior features like Eye Aspect Ratio, Mouth Opening Ratio, and Nose Length Ratio. The system, employing SVM and Bayesian classifiers, shows high accuracy, with future implementation in vehicles proposed for real-life validation [20].

Ananya Bhavana D S et al., 2021 examines a real-time algorithm for detecting driver fatigue through eye-blink and yawn detection using facial landmark detectors. The system utilizes the eye aspect ratio (EAR) to accurately identify eye and mouth openings in video frames. If the driver is detected as asleep, a warning alarm is triggered. Experimental results demonstrate the high accuracy and robustness of the proposed method in varying conditions[21].

Ankit Sonje et al., 2021 examines a This paper addresses the reduction of accidents caused by driver distraction and drowsiness due to sleep deprivation. We implement real-time monitoring of the driver's face using a Pi camera and the Eye Aspect Ratio (EAR) algorithm to detect drowsiness. If detected, an alarm is triggered, a message is sent to the user, and the vehicle's ignition is turned off. This approach aims to mitigate accident risks through real-time drowsiness and distraction detection[22].

III. METHODOLOGY

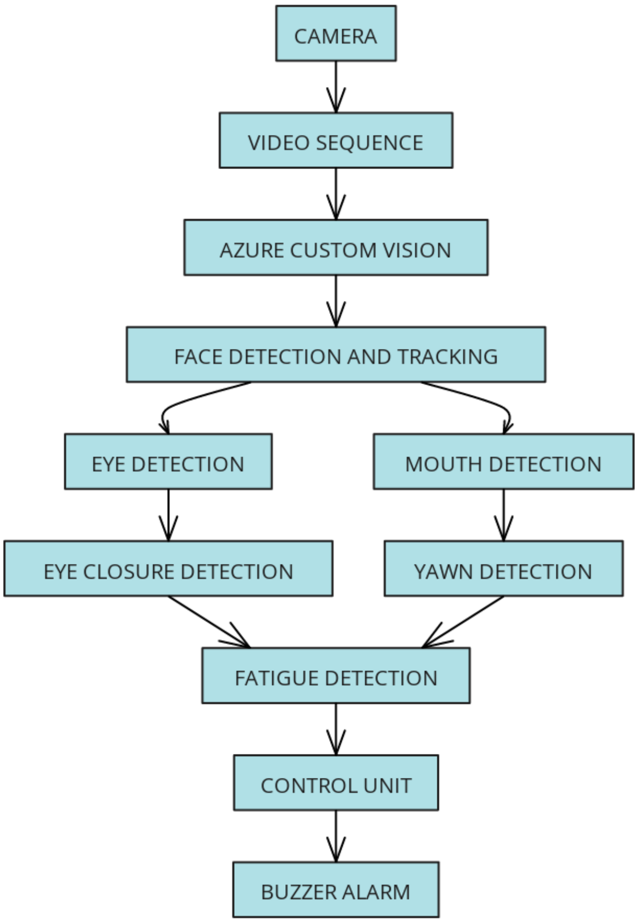

Fig. 1. Proposed system block diagram

Fig 1 illustrates the block diagram of the proposed model. The initial phase involves data collection and preparation. This is followed by model selection, training, and validation procedures. Next, the trained model is evaluated. The final phase includes assessing the classification model and testing it using an image file

The Azure Custom Vision Classification Model is a powerful tool within Microsoft Azure's suite of AI services, designed for image classification tasks. It allows users to train custom image classification models using their own datasets, enabling high accuracy in recognizing specific objects or patterns. The process begins by uploading labeled images, which the model uses to learn and differentiate between categories. The model employs machine learning algorithms to analyze these images, generating a model that can classify new, unseen images. Users can fine-tune the model through iteration, enhancing its accuracy and robustness. Azure Custom Vision supports both cloud-based and edge deployment, making it versatile for various applications, from real-time object detection in mobile apps to industrial automation. Its integration with Azure's infrastructure ensures scalability, security, and seamless integration with other Azure services, offering a comprehensive solution for developers and businesses seeking custom image recognition capabilities.

Fig. 2. Sample dataset for driver drowsiness detection

A. *Gathering of datasets*

The system initiation involves the compilation of datasets. As depicted in Figure 2, data images will serve as the foundation for constructing the Classification system. These datasets[23] are sourced from Kaggle, a dataset repository. Training and validation will be conducted utilizing the AZURE Custom Vision pretrained algorithm. The study incorporates a total of 2900 images, with an 75% allocation for training and 25% for validation.

B. *Data Preprocessing*

After collecting the image datasets and uploading them to Custom Vision, tags were created for different categories of images, such as "drowsy" and "wakeful." This systematic labeling helps in clearly identifying each group for training and analysis. Accurate tagging enhances the model's ability to distinguish between these states, improving the performance and accuracy of the classification model.

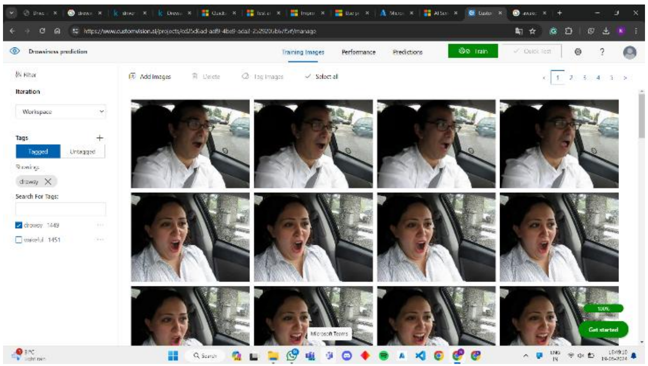

Fig. 3. Ground truth labeling of the dataset .

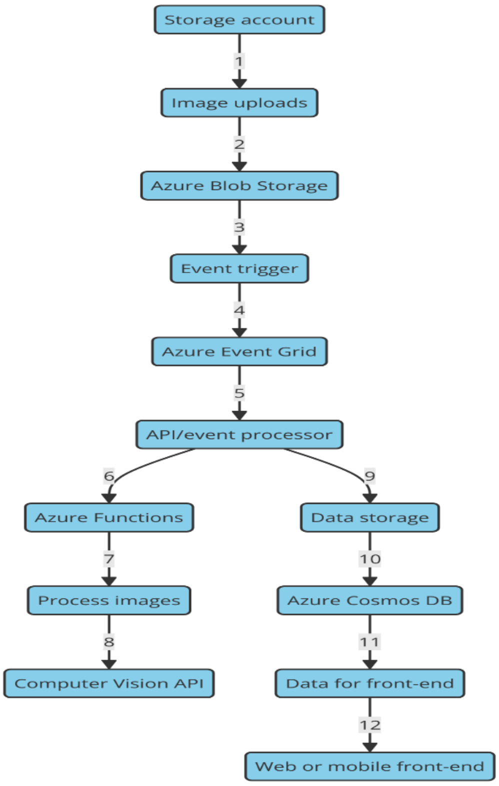

Fig. 4. AZURE Custom Vision object detection framework.

C. *Training*

Training a Convolutional Neural Network (CNN) model using Azure Custom Vision involves an iterative process of uploading tagged images, training the model, and refining the parameters to enhance accuracy. The CNN model, utilizing the VGG16 architecture, will be trained to classify images as either "Drowsy" or "Wakeful" based on facial expressions and eye states. To start, tagged images of faces clearly showing differences between drowsy and wakeful states are uploaded to Azure Custom Vision.

The system preprocesses these images to a standardized input size of 224x224x3, ensuring uniformity in the training data. As the training progresses, the model's performance can be monitored through Azure's intuitive dashboard, which displays key metrics such as accuracy, precision, recall, and loss. Each training iteration is crucial for improving the model, especially when using the VGG16 architecture. After the initial training round, it's important to review the results to identify any weaknesses in the model's performance. VGG16, with its 16 convolutional and pooling layers, is known for its deep learning capabilities in analyzing and classifying images. This review process may reveal the need to add more images to balance the dataset, refine existing tags for better clarity, or adjust training parameters like learning rates or batch sizes. By analyzing the confusion matrix and other diagnostic tools provided by Azure, areas where the VGG16-based model struggles can be identified, leading to targeted improvements. Iterative refinement ensures the model becomes progressively more accurate in distinguishing between drowsy and wakeful states, leveraging VGG16's hierarchical feature extraction. This approach combines the power of deep learning and the VGG16 architecture with cloud computing to develop a reliable and efficient drowsiness detection system capable of real-time facial expression and eye state analysis.

D. Testing

The test data will upload to the custom vision model through the provided interface. The model analyzed the image to predict the driver's state as either "wakeful" or "drowsy."

IV. Results and Discussions

A. Results of Training and Validation

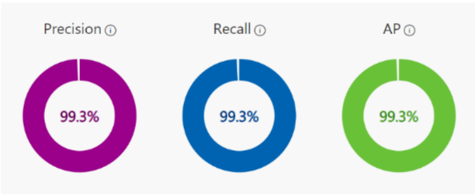

Fig.5

Performance of the proposed model

In Fig. 5, the graphical depiction illustrates the training and validation outcomes of the dataset. The final results show a Precision, Recall, and Average Precision of 99.3%.

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B. Model Evaluation

The performance metrics of the model are highly promising, as demonstrated in the provided table I. Overall, the model demonstrates an impressive Precision, Recall, and Average Precision (AP) of 99.3%. These values demonstrate that the model is both highly accurate in its predictions and consistent in identifying the relevant instances across the dataset. The second figure breaks down the performance per tag, providing more granular insights. For the "wakeful" tag, the model achieved a Precision of 98.6% and a perfect Recall of 99.3%, resulting in an AP of 99.1%. This indicates that while the model occasionally makes false positives, it successfully identifies all true positive instances of wakefulness.

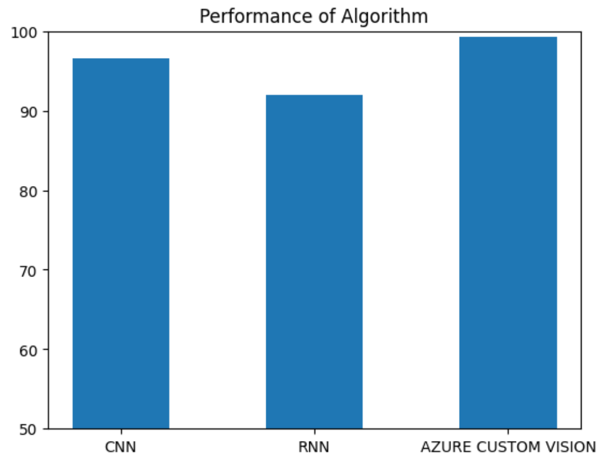


Fig. 6. Compared with existing algorithm

The bar chart compares the performance of three algorithms—CNN, RNN, and Azure Custom Vision—in driver drowsiness detection. CNN, with an accuracy of approximately 96.51%, is likely used for analysing visual cues such as eye closure or facial expressions to detect drowsiness. Its high accuracy reflects its effectiveness in image-based tasks, making it well-suited for this application.

RNN, which processes sequential data, achieved around 92% accuracy, slightly lower than CNN. This suggests it might be used to analyze time-based data like blinking patterns or head movements. Azure Custom Vision, with a 99.3% accuracy, likely uses a combination of visual recognition and machine learning techniques, demonstrating superior performance in this specific context.

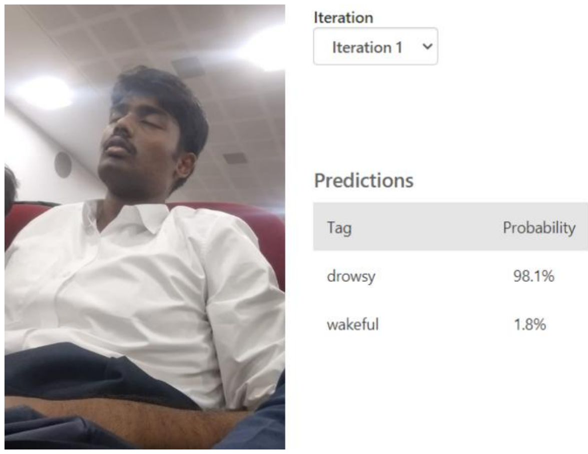
Table I. Performance Per Tag

Tag	**Precision**	**Recall**	**AP**	**Image count**
Wakeful	98.6%	99.8%	99.1%	1451
Drowsy	99.8%	98.6%	99.5%	1449

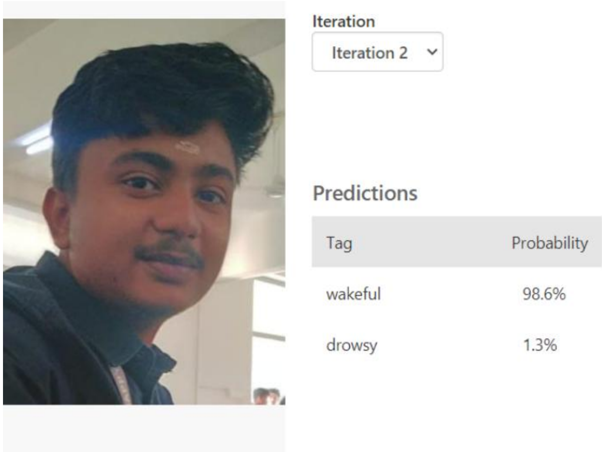
For the "drowsy" class, the model achieved a perfect Precision of 98%, meaning all predicted drowsy instances are correct, with a Recall of 99.3%, resulting in an AP of 99.3%. This implies that the model is slightly less effective in identifying all true instances of drowsiness but is highly accurate when it does. The balanced image count for both tags, with 1451 for "wakeful" and 1449 for "drowsy", ensures a fair evaluation of the model's performance. The presented metrics collectively highlight the model's robustness and reliability in differentiating between wakeful and drowsy states. This underscores its value for applications requiring high precision and recall.

Evaluation of Model

This accuracy ranges from 40% to 89%, culminating in an overall testing accuracy of 99.3%, indicating precise detection of the driver's level of eye drowsiness. Enhancing the detection accuracy within the 40% to 89% range may be achieved through the augmentation of additional datasets



(a)



(b)

Fig. 7. Testing result of image (a),(b).

V. CONCLUSION AND FUTURE WORKS

The research indicates that a Convolutional Neural Network (VGG16) is used to diagnose eye drowsiness and yawning behavior, which can help deter road crashes due to driver fatigue or exhaustion. The study employs Azure Custom Vision, which utilizes the pre-trained CNN VGG16 algorithm. The model generated and used by the study achieved a mean Average Precision value of 99.3% and a recall value of 99.3%. With this, the final testing achieves 99.9% accuracy, correctly and accurately detecting all presented images during testing. As the research suggests eye drowsiness detection for drivers, enhancing the system could involve integrating an additional dataset capable of detecting driver yawning through image analysis. Hardware can also be included in the system, such as a camera integrated with an alarm, which activates every time the camera detects driver drowsiness.

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