Driver Drowsiness Detection System

Driver fatigue is a major cause of road accidents worldwide. This project presents a real-time Driver Drowsiness Detection System that leverages Convolutional Neural Networks (CNNs) and computer vision to monitor a driver's facial expressions and determine their level of alertness.

The system utilizes a laptop camera to continuously capture live video frames, which are then processed to detect the driver's eye state—whether open or closed. If the system detects prolonged eye closure, it interprets this as drowsiness and triggers an audible alarm to alert the driver.

Supporting Literature: DriCare System

Real-Time Detection

W. Deng and R. Wu developed a Real-Time Driver-Drowsiness Detection System using facial features to identify signs of fatigue, such as eye closure, blinking frequency, and yawning.

Non-Contact Solution

The system, called DriCare, is designed as a non-contact solution using a camera and deep learning techniques, avoiding the need for wearable sensors.

High Accuracy

Experimental results show that DriCare achieves around 92% accuracy, making it a reliable and practical solution for road safety.

Findings and Proposals for Improvement

Effective Method

CNN-based driver drowsiness detection is a highly effective method for monitoring driver alertness in real-time, achieving high accuracy with minimal computational overhead.

Areas for Improvement

The current system focuses solely on eye state detection and may experience reduced accuracy when drivers wear glasses or encounter extreme lighting variations.

Proposed Enhancements

Inclusion of facial expression analysis and head position tracking can provide a more comprehensive measure of driver fatigue, enhancing system capabilities.

Dataset Analysis

1

Dataset Composition

The Driver Drowsiness Detection Model classifies eye images into two categories: Open and Closed, using an open-source dataset for training and testing.

2

Dataset Structure

The dataset is organized into train and test folders, each containing subfolders for Open and Closed eyes, ensuring structured data management.

3

Dataset Size

The dataset consists of 35,381 images labeled across two classes, with a split of 70:30 for training and testing, ensuring balanced distribution.

Data Preprocessing Techniques

1

Image Resizing

Images are resized to 64x64x3 pixels to ensure consistency across the dataset and real-time detection, improving accuracy and efficiency.

2

Data Augmentation

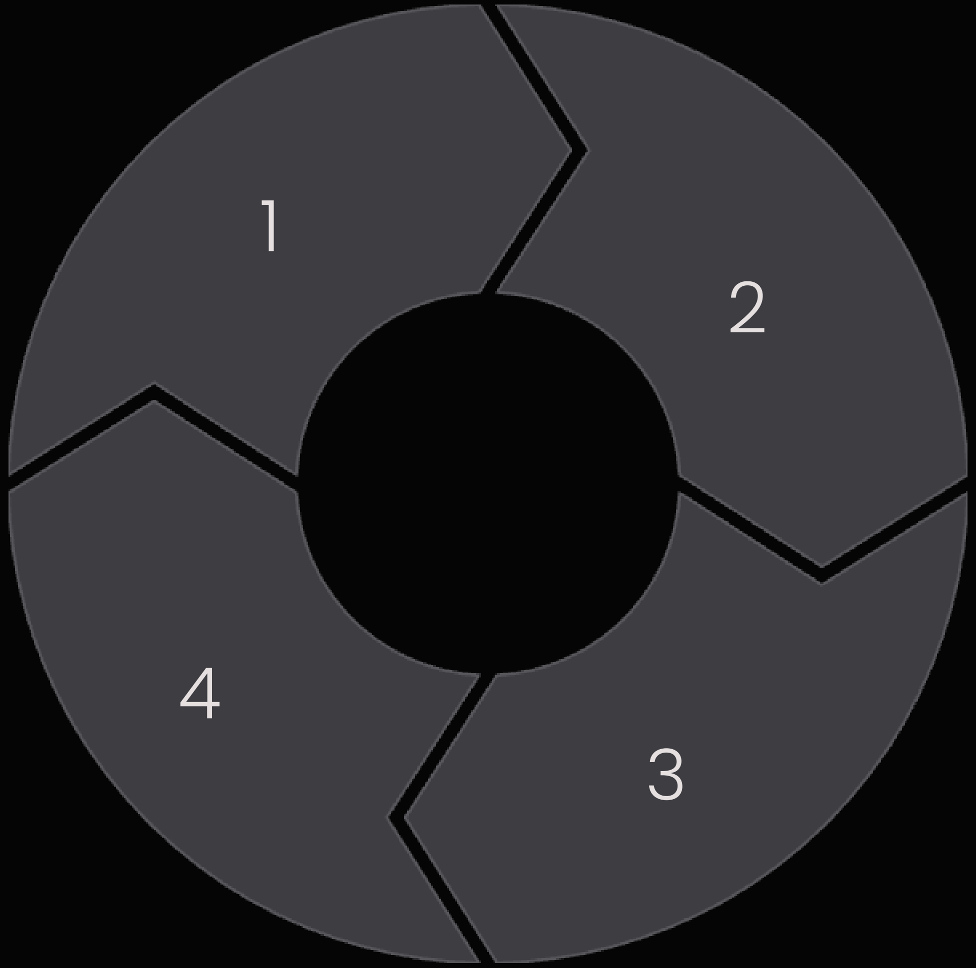
ImageDataGenerator is used for preprocessing and augmentation, including rescaling, rotating, shifting, and flipping images to enhance model performance.

3

Feature Extraction

OpenCV extracts the eye region, converts it to RGB, resizes, and normalizes it before passing it to the CNN model for classification, ensuring standardized data input.

CNN Architecture Analysis



Convolutional Layers

The model begins with Conv2D layers, using 32, 64, and 128 filters to capture basic and complex image features.

MaxPooling Layers

MaxPooling2D layers reduce spatial dimensions, improving computational efficiency and retaining important features.

Dense Layers

A Dense layer with 256 neurons learns high-level representations, followed by a Dropout layer to prevent overfitting.

Output Layer

The final layer uses a sigmoid activation function to classify the image as either open or closed, providing a probability score.

Feasibility Analysis

1. ### Technical

   Requires webcam, CPU/GPU, memory.

2. ### Economic

   Cost-effective due to open-source tools.

3. ### Operational

   Partially operational, basic detection.

The Driver Drowsiness Detection System is analyzed for technical, economic, and operational feasibility. While technically feasible with a webcam and sufficient processing power, it is cost-effective due to the use of open-source libraries. Operationally, it provides basic drowsiness detection but requires further enhancements for real-world deployment.

Conclusion and Future Work

1 Effective Classification

The model successfully classifies eye states, achieving 80% accuracy, demonstrating its capability to detect drowsiness effectively.

2 Potential Enhancements

Future improvements could include integrating head pose detection, yawning recognition, and real-time monitoring with video input.

3 Real-World Application

Expanding the dataset and further fine-tuning the model will contribute to better performance in real-world driving conditions, enhancing road safety.