PROJECT REPORT: COMPUTER VISION LAB

Distracted Driver Detection

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Abstract:

Road safety is a critical concern globally, with distracted driving being a major cause of accidents. This project explores the development of a camera-based monitoring system for insured vehicles to enhance road safety. Using an Convolutional Neural Network (CNN)-based model, the system classifies driver behaviors in real-time. Key results include high classification accuracy (98%) and robust generalization, showcasing the feasibility of implementing this solution for reducing accidents and improving insurance processes. This project has significant implications for promoting safer driving habits and enhancing the efficiency of claims processing.

Introduction

Road safety is a critical concern globally, with distracted driving being a major cause of accidents. Vehicle insurance companies are exploring innovative solutions to enhance monitoring and reduce accident rates. Implementing cameras on insured vehicles presents a promising approach. This project investigates the feasibility, methodology, and potential benefits of deploying camera systems in insured vehicles to monitor driver behavior, improve real-time response, and facilitate efficient claims processing.

Objective

The objective of this project is to develop and implement a camera-based monitoring system for insured vehicles. The goals are to:

1. Enhancing real-time monitoring of driver behavior.

2. Improving accuracy in identifying causes of accidents.

3. Facilitating efficient claims processing and fraud detection.

4. Promoting safer driving habits among policyholders.

Problem Description

What?

Distracted driving is a significant contributor to road accidents, leading to severe injuries and fatalities. Traditional methods of monitoring driver behavior rely heavily on manual observation, which is labor-intensive, time-consuming, and often prone to human error. The lack of real-time capabilities in these methods further exacerbates the problem, as immediate intervention is crucial in preventing accidents.

Why?

The implementation of cameras on insured vehicles addresses several critical issues in road safety and insurance management. Automated monitoring systems provide continuous surveillance, enabling real-time detection and response to unsafe driving behaviors. This not only enhances road safety but also assists insurance companies in accurately identifying the causes of accidents, thereby improving the efficiency of claims processing and reducing fraudulent claims. Additionally, promoting safer driving habits among policyholders can lead to lower accident rates and reduced insurance premiums.

Methodology

Approach and Methods

The project employs an Artificial Neural Network (ANN)-based model to analyze images captured by the cameras. The methodological approach involves several key steps, each designed to ensure the accuracy and efficiency of the system:

1. **Loading Dataset**: Collecting a diverse dataset of driver behaviors from various sources, ensuring a wide range of driving conditions and behaviors are represented.

2. **Normalizing**: Standardizing the image data to ensure consistency in input, which is critical for the effective training of the neural network.

3. **Class Mapping**: Categorizing different types of distracted driving behaviors into predefined classes. This step is essential for the model to accurately classify and predict driver behaviors.

4. **Implementing Model**: Building the ANN model involves defining the architecture, including convolutional layers for feature extraction, pooling layers for downsampling, dropout layers to prevent overfitting, and dense layers for classification.

5. **Model Training**: Training the model on the collected dataset to optimize the weights and biases, ensuring high accuracy in classifying driver behaviors.

6. **Testing**: Evaluating the model's performance on a separate test dataset to validate its accuracy and generalizability.

7. **Prediction**: Using the trained model to predict driver behaviors in real-time, providing continuous monitoring.

8. **Deployment**: Implementing the camera and model system in insured vehicles, integrating with existing insurance company infrastructure for continuous monitoring and data analysis.
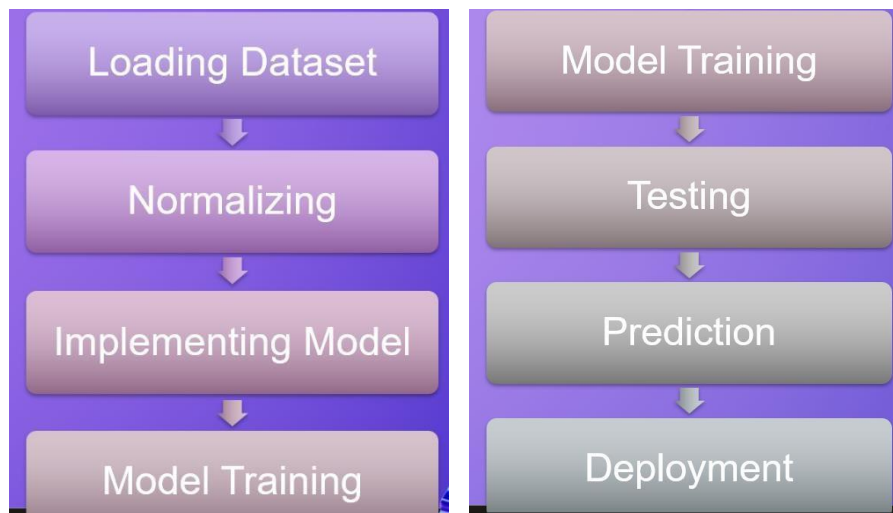
Tools and Libraries:

- Python
- TensorFlow
- OpenCV

Model Implementation and Working

The ANN model employed in this project consists of several key components:

1. **Convolutional Layers**: These layers are responsible for extracting local features from the input images. Each convolutional layer applies a set of filters to the input, producing feature maps that capture patterns such as edges, textures, and shapes.

2. **MaxPooling Layers**: MaxPooling layers reduce the spatial dimensions of the feature maps, retaining only the most important features. This downsampling process helps in reducing computational complexity and mitigating overfitting.

3. **Dropout Layers**: Dropout is a regularization technique used to prevent overfitting by randomly setting a fraction of the input units to zero during training. This helps in making the model more robust and generalizable.

4. **Flatten Layer**: This layer converts the 2D feature maps into a 1D vector, which can be fed into the dense layers for classification.

5. **Dense Layers**: The dense layers are fully connected layers that apply weights and biases to the input vector, using activation functions to make the final class predictions. The output layer uses a softmax activation function to produce probabilities for each class.

Project Scope

The project focuses on implementing a camera system for real-time monitoring of driver behavior in insured vehicles. The system stores data for 15 days, with an additional 5 days for compensation and deduction purposes. The boundaries include:

- Real-time video capture and processing.
- Classification of driver behaviors into predefined categories.
- Limited to vehicles insured by participating insurance companies.
- Data storage and retrieval for up to 20 days.

Privacy Concerns

Ensuring the privacy and security of collected data is paramount. The data is stored securely within the organization and accessed only for authorized purposes, such as claims processing and fraud detection. Measures include:

- **Encryption**: All data is encrypted during transmission and storage.

- **Access Control**: Strict access controls to prevent unauthorized access.

- **Data Anonymization**: Personal identifiers are anonymized to protect the identity of individuals.

- **Compliance**: Adherence to data protection regulations, such as GDPR.

Model Architecture

The model architecture for the distracted driver detection system is designed to effectively extract and classify features from input images, ensuring high accuracy in detecting various driving behaviors. The architecture follows a sequential model comprising several layers, starting with four convolutional layers (Conv2D), each followed by a max-pooling layer (MaxPooling2D). These convolutional layers, with 64, 128, 256, and 512 filters respectively, are responsible for detecting edges,

```
Model: "sequential"
```

Layer (type)	Output Shape	Param #
conv2d (Conv2D)	(None, 64, 64, 64)	640
max_pooling2d (MaxPooling2D)	(None, 32, 32, 64)	0
conv2d_1 (Conv2D)	(None, 32, 32, 128)	73,856
max_pooling2d_1 (MaxPooling2D)	(None, 16, 16, 128)	0
conv2d_2 (Conv2D)	(None, 16, 16, 256)	295,168
max_pooling2d_2 (MaxPooling2D)	(None, 8, 8, 256)	0
conv2d_3 (Conv2D)	(None, 8, 8, 512)	1,180,160
max_pooling2d_3 (MaxPooling2D)	(None, 4, 4, 512)	0
dropout (Dropout)	(None, 4, 4, 512)	0
flatten (Flatten)	(None, 8192)	0
dense (Dense)	(None, 500)	4,096,500
dropout_1 (Dropout)	(None, 500)	0
dense_1 (Dense)	(None, 10)	5,010

```
Total params: 5,651,334 (21.56 MB)
Trainable params: 5,651,334 (21.56 MB)
Non-trainable params: 0 (0.00 B)
```

textures, and other significant features within the images. The max-pooling layers reduce the spatial dimensions of the feature maps, which helps in minimizing computational complexity and avoiding overfitting. Following these layers, a dropout layer is introduced to further prevent overfitting by randoml y setting 50% of the neurons to zero during training. The feature maps are then flattened into a

1D vector by the flatten layer, which is passed through a dense layer with 500 units and ReLU activation to learn complex representations. Another dropout layer is applied before the final dense layer with 10 units and a softmax activation function, which outputs the probabilities for each of the ten classes of distracted driving behaviors. The model, totaling 5,651,334 parameters, is meticulously designed to balance complexity and performance, ensuring robust classification of driver behaviors for enhanced road safety.

RESULTS:

Accuracy Graphs

The accuracy graph illustrates the performance of the model over five training epochs, showcasing both training and validation accuracy. Initially, the training accuracy increases sharply, indicating that the model is quickly learning from the data. By the third epoch, the training accuracy approaches 1.0, demonstrating that the model has effectively learned the training data. The validation accuracy also shows a consistent upward trend, stabilizing around 0.98 after the second epoch. This indicates that the model generalizes well to unseen data, maintaining high accuracy and suggesting that overfitting is well-controlled.

The close alignment between training and validation accuracy curves further supports the model's'robustness and reliability in classifying distracted driving behaviors.
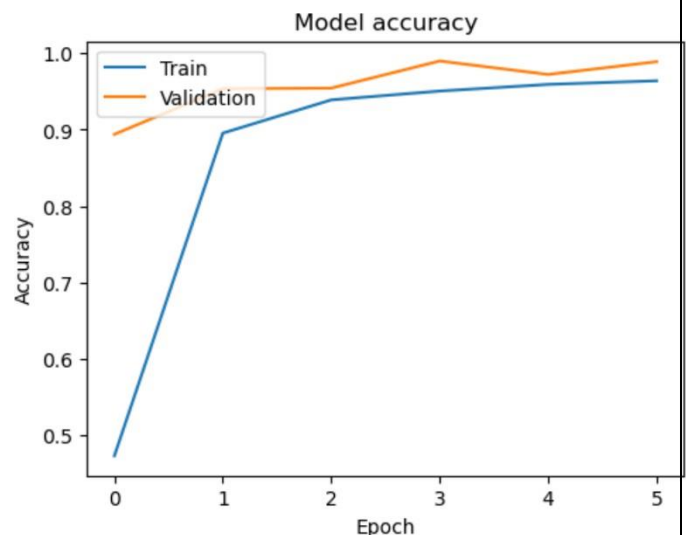
Loss Graph

The loss graph provides insights into the model's learning process over five training epochs, showing both training and validation loss. Initially, there is a steep decline in training loss, indicating that the model is rapidly learning and minimizing errors. By the second epoch, the training loss significantly decreases and stabilizes near zero, reflecting the model's efficiency in learning the training data. The validation loss also shows a consistent downward trend, stabilizing at a low value, which suggests that the model maintains its performance on unseen data without overfitting. The close convergence of training and validation loss values further confirms the model's robustness and its ability to generalize well across different datasets, reinforcing the effectiveness of the implemented architecture and training methodology.

GUI

Uploaded Image

Classifying...

Predicted Activity: Talking on the phone - right
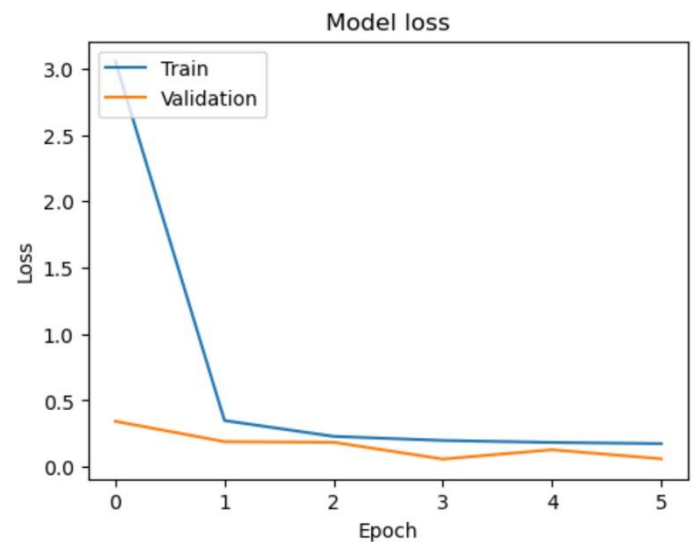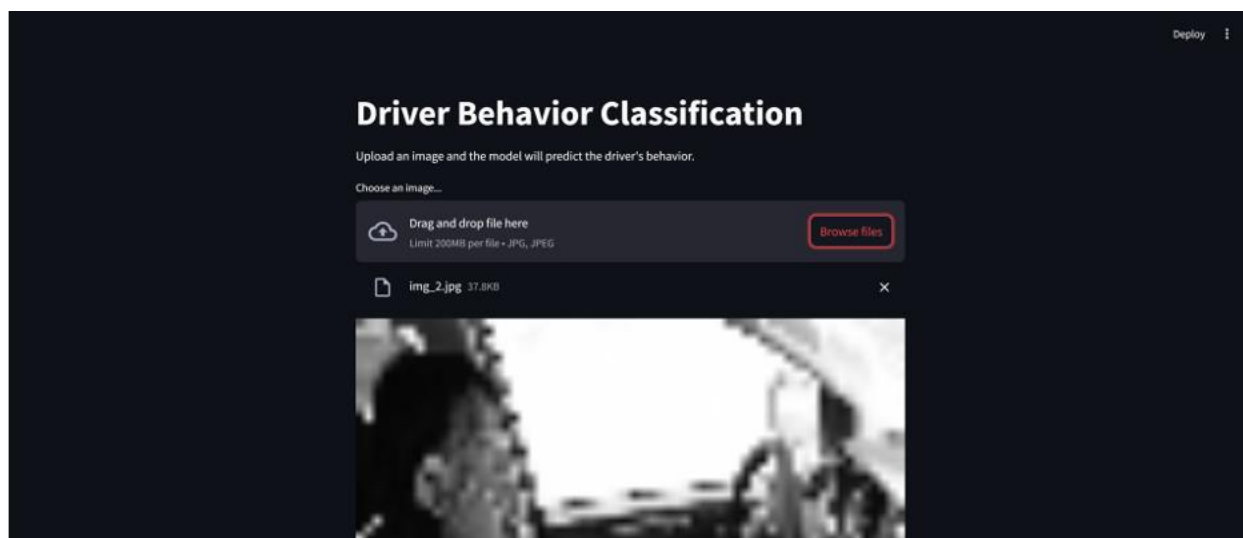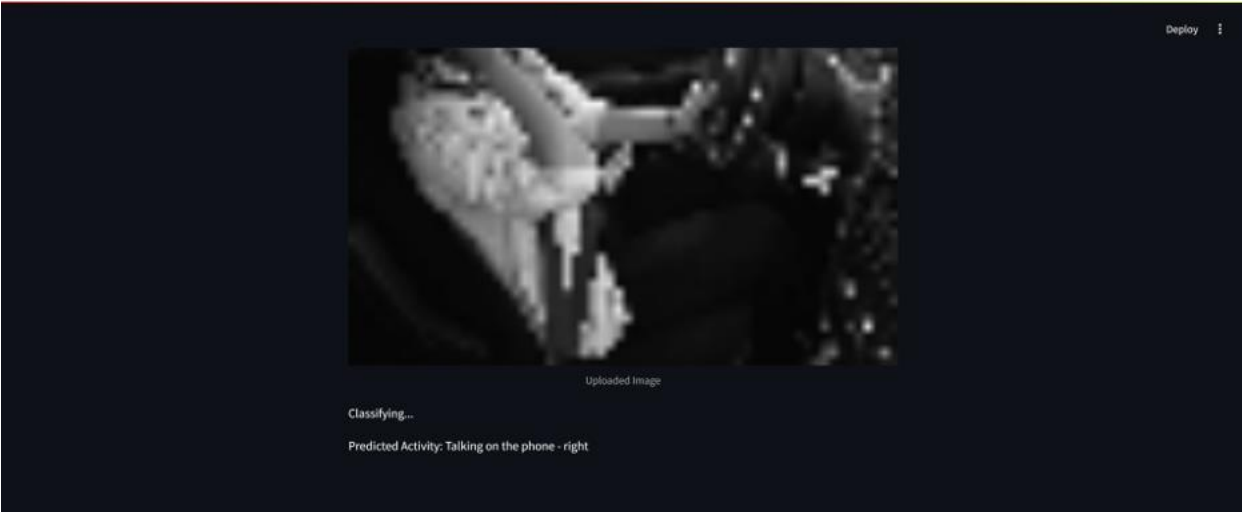
```
141/141 ───────────────── 30s 215ms/step
                              precision    recall  f1-score   support

                Safe driving       0.98      0.99      0.99       463
              Texting - right       0.99      0.99      0.99       500
 Talking on the phone - right       0.99      1.00      0.99       480
               Texting - left       0.99      1.00      1.00       491
  Talking on the phone - left       0.99      1.00      0.99       466
          Operating the radio       1.00      0.99      0.99       466
                     Drinking       0.99      1.00      0.99       457
              Reaching behind       0.99      0.98      0.99       377
              Hair and makeup       0.98      0.99      0.98       390
          Talking to passenger       0.99      0.98      0.98       395

                     accuracy                          0.99      4485
                    macro avg       0.99      0.99      0.99      4485
                 weighted avg       0.99      0.99      0.99      4485
```
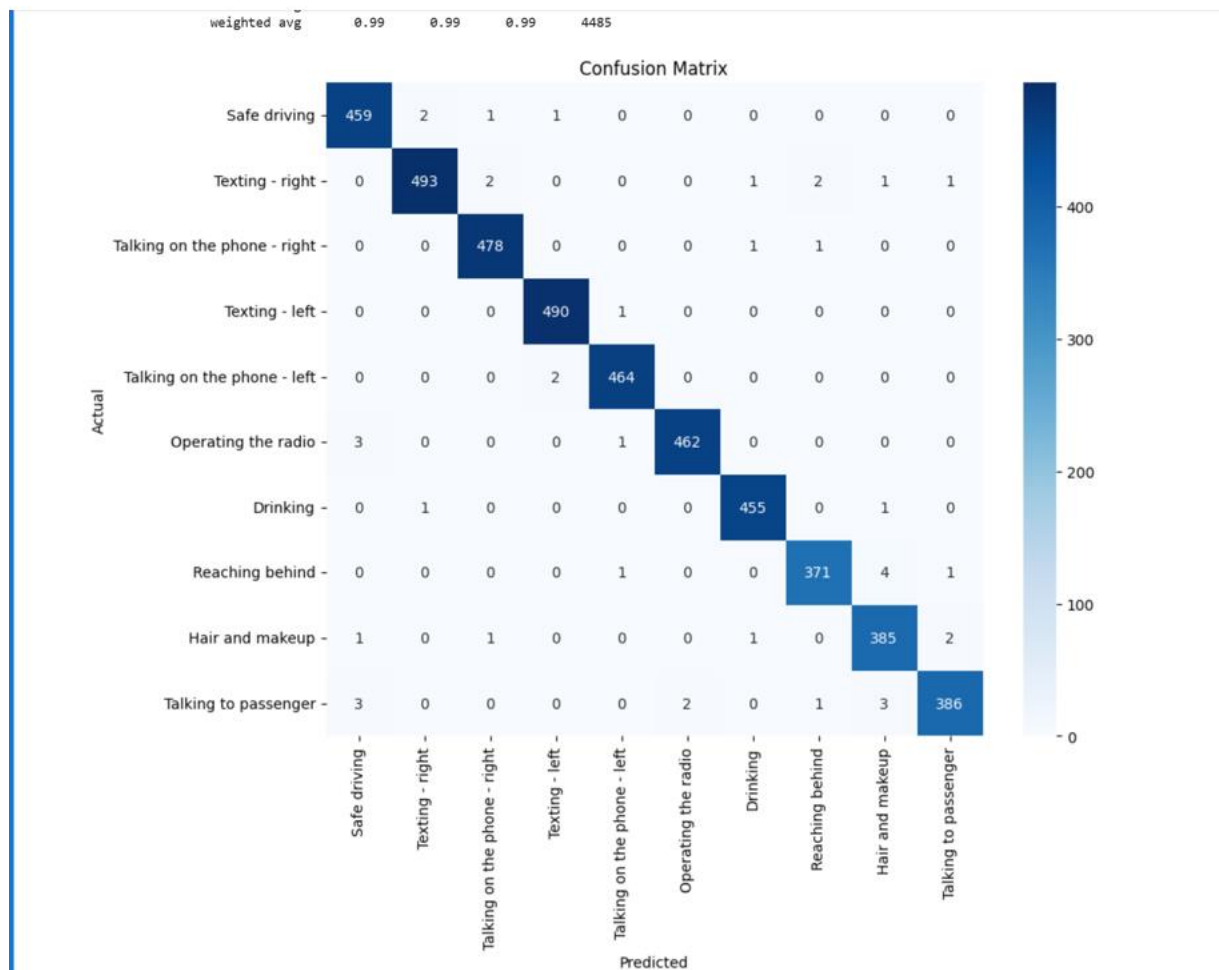
Confusion Matrix

Actual \ Predicted	Safe driving	Texting - right	Talking on the phone - right	Texting - left	Talking on the phone - left	Operating the radio	Drinking	Reaching behind	Hair and makeup	Talking to passenger
Safe driving	459	2	1	1	0	0	0	0	0	0
Texting - right	0	493	2	0	0	0	1	2	1	1
Talking on the phone - right	0	0	478	0	0	0	1	1	0	0
Texting - left	0	0	0	490	1	0	0	0	0	0
Talking on the phone - left	0	0	0	2	464	0	0	0	0	0
Operating the radio	3	0	0	0	1	462	0	0	0	0
Drinking	0	1	0	0	0	0	455	0	1	0
Reaching behind	0	0	0	0	1	0	0	371	4	1
Hair and makeup	1	0	1	0	0	0	1	0	385	2
Talking to passenger	3	0	0	0	0	2	0	1	3	386

DISCUSSION:

Analysis: The model effectively classifies driver behaviors with high accuracy and generalization. Challenges included data diversity and ensuring real-time performance, addressed through optimized preprocessing and architecture design.

Limitations:

- Limited to daytime operation.
- Requires further testing for diverse driving scenarios.

Future Work:

- Incorporate night vision capabilities.

- Add facial recognition for more detailed behavior analysis.
- Explore dynamic camera positioning.

Conclusion

The implementation of cameras on insured vehicles provides a robust solution for enhancing road safety and improving insurance processes. The project successfully demonstrates the feasibility of using ANN models to monitor and classify driver behaviors in real-time. The system not only aids in reducing accidents but also streamlines claims processing and fraud detection. Future work will focus on expanding the system's capabilities to include night vision, facial recognition, and dynamic camera detection to further enhance its effectiveness.

REFERENCES

https://github.com/Hasaan059/Computer-Vision.git

https://www.kaggle.com/code/kaustubhshirpurkar/distracted-driver-detection

https://www.linkedin.com/in/farhan-ahmad-0141a728b?utm_source=share&utm_campaign=share_via&utm_content=profile&utm_medium=ios_app