DRIVER DROWSINESS DETECTION USING DEEP LEARNING

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Introduction

Drowsy driving is a major safety hazard, causing an estimated 100,000 police-reported crashes, 50,000 injuries, and 800 fatalities annually according to the NHTSA. Furthermore, drowsiness is responsible for 21% of fatal collisions, and 60% of drivers admit to driving while fatigued. This study explores a deep learning-based method to detect driver fatigue using live data from an in-car camera, analyzing eye activity, head movements, and facial expressions. By evaluating three pre-trained deep learning architectures (InceptionV3, EfficientNetB2, and MobileNetV2) and comparing single and ensemble models, we aim to enhance non-invasive, economical driver drowsiness detection systems, ultimately contributing to safer roads and reducing collisions.

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Literature Survey

Paper Name	Method Used	Conclusion
Driver Drowsiness Detection using Deep Learning [3]	CNN Model	Accuracy of 86.05%
Driver Drowsiness Detection by Applying Deep Learning Techniques to Sequences of Images [2]	Convolutional recurrent neural network, fuzzy logic based system	65% on training 60% on test, 93% on fuzzy
An Efficient Driver Drowsiness Detection Using Deep Learning [4]	Detects driver drowsiness using EEG signals.	Required drivers to wear a hand band, which was tedious.
Drowsy Driver Detection Using Two Stage Convolutional Neural Networks [1]	YOLOv3 for face detection and InceptionV3 for drowsiness detection	Accuracy of 89.90%
Sddd: Stacked ensemble model for driver drowsiness detection [5]	SqueezeNet, ShuffleNet, and MobileNet-V2	Highest accuracy of 86.1%

Table 1: Comparison of different driver drowsiness detection methods

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Problem Statement

- To evaluate different models and architectures for the efficient analysis of driver drowsiness detection system.
- To develop CNN models for driver drowsiness detection that enhance accuracy and improve road safety by reliably identifying signs of driver fatigue.

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Proposed Methodology

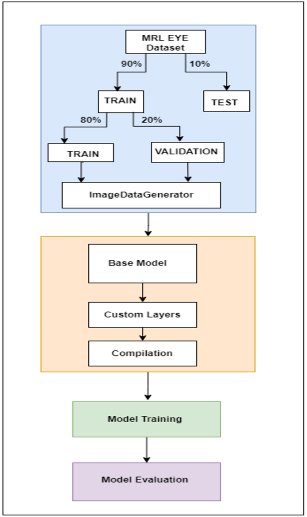

Figure 1: Proposed Methodology

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Media Research Lab (MRL) Eye dataset is used for this study.

Few images from this dataset is shown below.

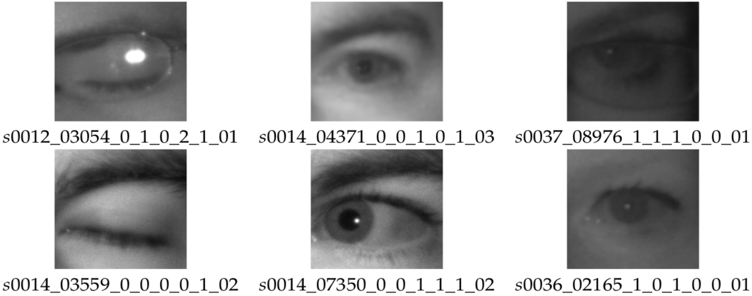

Figure 2: MRL Eye Dataset

Dataset

s0012_03054_0_1_0_2_1_01

s0014_07350_0_0_1_1_1_02

- 84,898 images
- subject ID
- image ID
- gender
- glasses
- eye state
- reflections
- lighting conditions
- sensor ID (640 x 480, 1280 x 1024, 752 x 480)

Dataset

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Pre-Processing

Pre-Processing

- Dataset is divided into:
  - train (90%)
  - test (10%)
- train data is again splitted into:
  - train (80%)
  - validation (20%)
- Data Augmentation
  - Rescaling
  - Rotation Range
  - Shear Zoom
  - Zoom Range
  - Width Shift Range
  - Height Shift Range
- input image is set to 80x80x3 resolution.

Implementation

Stand-Alone Models:

- InceptionV3
- EfficientNetB2
- MobileNetV2

Stacked Ensemble:

InceptionV3 + EfficientNetB2 + MobileNetV2

Model Details:

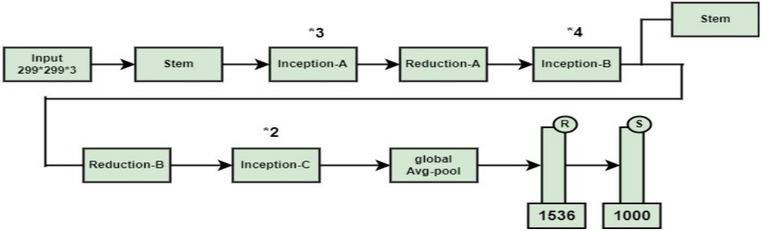

Figure 3: InceptionV3 Architecture

InceptionV3

- 48 layers
- 24 million parameters
- Inception modules(1x1, 3x3, 5x5 convolutions)

Model Details:

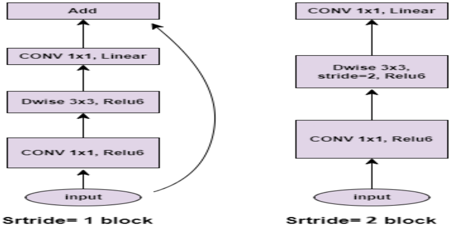

Figure 4: MobileNetV2 Architecture

MobileNetV2

- 53 layers
- 3.4 million parameters
- Lightweight Model

Model Deatils:

EfficientNetB2

- 130 layers
- 9.2 million parameters
- MBConv Blocks

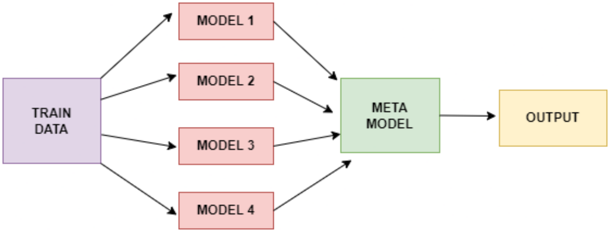

Figure 5: Stacked Ensemble Model

Stacked Ensemble Model

InceptionV3 + EfficientNetB2 + MobileNetv2

Customizations:

Stand-Alone Model

- Flatten Layer
- Dense Layer (64 units)
- Dropout Layer (0.2)
- Dense Layer

Stacked Ensemble:

- Base Models
- GlobalAveragePooling2D
- Concatenation
- BatchNormalization layer
- Dropout Layer (0.2)
- Dense Layer

Customizations

Hyperparameters and Callbacks:

- batchsize: 8
- epochs: 10
- Optimizer: Adam
- loss: Binary Crossentropy
- EarlyStopping : val_loss
- ReduceLROnPlateau : val_loss

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InceptionV3:

Activation Function	Training Accuracy	Training Loss
RELU	0.9568	0.1161
Leaky_ReLU	0.9495	0.1320
selu	0.9567	0.1147
Relu6	0.9382	0.1564
silu	0.9411	0.1515
gelu	0.9410	0.1525

Table 2: InceptionV3's Training Accuracy and Training Loss

Activation Function	Val Accuracy	Val Loss
RELU	0.9100	0.2350
Leaky_ReLU	0.9117	0.2233
selu	0.9051	0.2527
Relu6	0.9034	0.2343
silu	0.9012	0.2456
gelu	0.9020	0.2208

Table 3: InceptionV3's Validation Accuracy and Validation Loss

Results:

Activation Function	Test Accuracy	Test Loss
RELU	0.9488	0.1327
Leaky_ReLU	0.9542	0.1278
selu	0.9577	0.1211
Relu6	0.9488	0.1327
silu	0.9456	0.1452
gelu	0.9467	0.1403

Table 4: InceptionV3's Test Accuracy and Test Loss

EfficientNetB2:

Activation Function	Training Accuracy	Training Loss
RELU	0.6434	0.4287
Leaky_ReLU	0.6523	0.4312
selu	0.6513	0.4211
Relu6	0.6612	0.3825
silu	0.6264	0.4633
gelu	0.6234	0.4473

Table 5: EfficientNetB2's Training Accuracy and Training Loss

Results:

Activation Function	Val Accuracy	Val Loss
RELU	0.6123	0.4322
Leaky_ReLU	0.6212	0.4421
selu	0.6624	0.4623
Relu6	0.6223	0.3712
silu	0.6032	0.3823
gelu	0.6112	0.4208

Table 6: EfficientNetB2's Validation Accuracy and Validation Loss

Activation Function	Test Accuracy	Test Loss
RELU	0.6231	0.4623
Leaky_ReLU	0.6543	0.4234
selu	0.6312	0.4211
Relu6	0.6253	0.3921
silu	0.6242	0.4532
gelu	0.6246	0.4112

Table 7: EfficientNetB2's Test Accuracy and Test Loss

MobileNetV2:

Activation Function	Training Accuracy	Training Loss
RELU	0.9425	0.1431
Leaky_ReLU	0.9421	0.1340
selu	0.9423	0.1237
Relu6	0.9354	0.1544
silu	0.9421	0.1235
gelu	0.9354	0.1465

Table 8: MobileNetV2's Training Accuracy and Training Loss

Activation Function	Val Accuracy	Val Loss
RELU	0.9160	0.2270
Leaky_ReLU	0.9187	0.2433
selu	0.9081	0.2647
Relu6	0.9054	0.2753
silu	0.9022	0.2566
gelu	0.9060	0.2278

Table 9: MobileNetV2's Validation Accuracy and Validation Loss

Results:

Activation Function	Test Accuracy	Test Loss
RELU	0.9458	0.1427
Leaky_ReLU	0.9642	0.1268
selu	0.9527	0.1241
Relu6	0.9418	0.1537
silu	0.9386	0.1322
gelu	0.9427	0.1543

Table 10: MobileNetV2's Test Accuracy and Test Loss

Stacked Ensemble:

Activation Function	Training Accuracy	Training Loss
RELU	0.9513	0.1676
Leaky_ReLU	0.9558	0.1218
selu	0.9405	0.1556
ReLU6	0.9408	0.1609
silu	0.9323	0.1439
gelu	0.9421	0.1643

Table 11: Ensemble Model's Training Accuracy and Training Loss

Results:

Activation Function	Val Accuracy	Val Loss
RELU	0.9289	0.2206
Leaky_ReLU	0.9154	0.2853
selu	0.9340	0.2544
ReLU6	0.9241	0.2578
silu	0.9112	0.2524
gelu	0.9220	0.2743

Table 12: Ensemble Model's Validation Accuracy and Validation Loss

Activation Function	Test Accuracy	Test Loss
RELU	0.9557	0.1992
Leaky_ReLU	0.9510	0.1494
selu	0.9621	0.1395
ReLU6	0.9505	0.1585
silu	0.9494	0.1432
gelu	0.9581	0.1893

Table 13: Ensemble Model's Test Accuracy and Test Loss

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Conclusion

Conclusion

- Successful integration of state-of-the-art methodologies for driver drowsiness detection.
- Highest accuracies obtained:
  - InceptionV3: 95.77%
  - EfficientNetB2: 65.43%
  - MobileNetV2: 95.27%
  - Stacked Ensemble Model: 96.21%

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Future Work

- Investigating more complex CNN designs, including recurrent neural networks (RNNs) or attention mechanisms, can provide better temporal modeling and context-aware sleepiness detection capabilities.
- The adaptability and responsiveness of the model can be improved by using adaptive learning systems that dynamically modify model parameters and thresholds in response to real-time feedback and driver behavior patterns.
- Low-latency inference and real-time decisionmaking can be made possible by integrating the sleepiness detection model with edge computing platforms or onboard vehicle technologies. This improves the system's usefulness in realistic driving circumstances.

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Thank you for your attention

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