Driver Behavior Detection

Arshad Shaik
Bhavana Mysore Basavaraju
Hemanth Reddy Devarapalli
Mohammed Abdul Azeez Ansari
Naga Sowmya Vaddempudi

Motivation

- Driving behavior is a major factor in road safety. Aggressive, distracted, or drowsy driving can lead to accidents and fatalities.

- Early detection of risky behaviors can mitigate these risks.

- This project aims to detect and categorize dangerous driving behaviors in real time using image data captured from within vehicles.

Importance of Driver Behavior

Driver behavior is a leading cause of road accidents: Distracted and unsafe behaviors such as texting, talking, and drowsiness contribute to a significant number of accidents globally.

Statistics: Over 90% of road traffic accidents are attributed to human error, with distracted driving accounting for approximately 25% of these.

Safety Impact: Monitoring and improving driver behavior can significantly reduce accident rates and save lives.

Research Questions

01 How can the dataset be preprocessed and organized to effectively train a deep learning model for driving activity classification?

02 What deep learning model architecture is suitable for classifying driving activities, and how can it be implemented?

03 How can data augmentation be applied to enhance the robustness and generalization of the model?

04 What training strategies and hyperparameters are needed to achieve optimal model performance?

Data

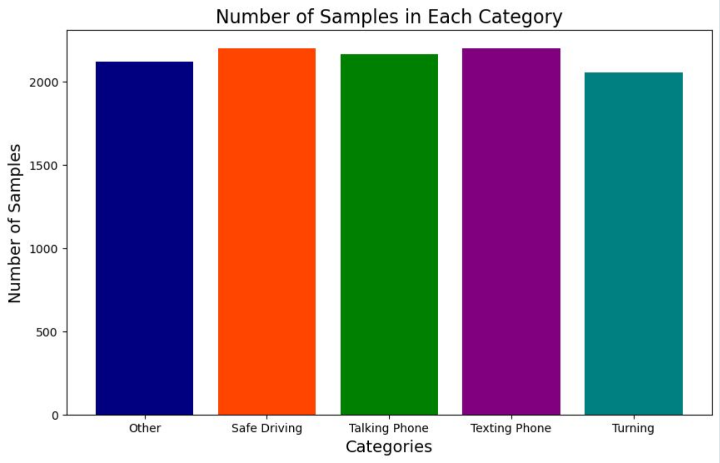
This dataset, includes drivers performing various tasks.

It is labelled into 5 driving behavior categories:

- Safe Driving: 2203
- Talking on the Phone: 2169
- Texting on the Phone: 2203
- Turning: 2057
- Other Activities: 2119

Format: Images in .png and .jpg formats
Total Images: 10,751

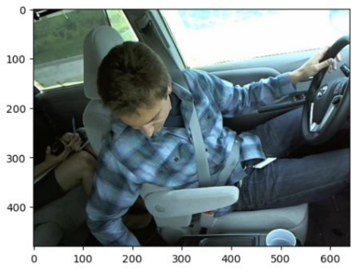
Class Distribution Consistency: Each class contributes approximately 20% of the total 10,751 images, with training (80% = 8,600), testing (10% = 1,075), and validation (10% = 1,075) preserving this ratio.



Data Preprocessing and Exploration

- Images are rescaled to the range [0, 1] to standardize input values, optimizing the learning process.
- A detailed class distribution analysis was conducted to ensure balanced data representation across training, testing, and validation sets.
- Random Image Selection (random.choice): Randomly picks images, ensuring diverse, unbiased inspection of the dataset.

Turning



Safe driving

Talking

Texting

Other

Approach

RESNET

- Built a custom ResNet34 architecture with convolutional layers, batch normalization, and skip connections for stable training and feature extraction.
- Included Global Average Pooling and Dropout layers to reduce overfitting and improve generalization.
- Added a Dense layer with Softmax activation for classifying 5 driver behavior categories.
- Used Adam optimizer and normalization to standardize input values, which enhances the model's learning process and robustness

Results

RESNET

Training vs. Validation Loss:

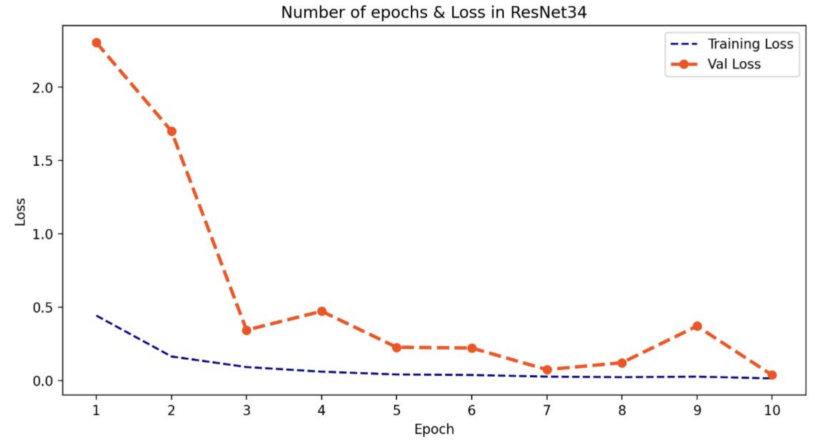
- Training loss decreased steadily, reaching close to 0 by the 10th epoch.
- Validation loss showed a consistent downward trend with minimal overfitting.

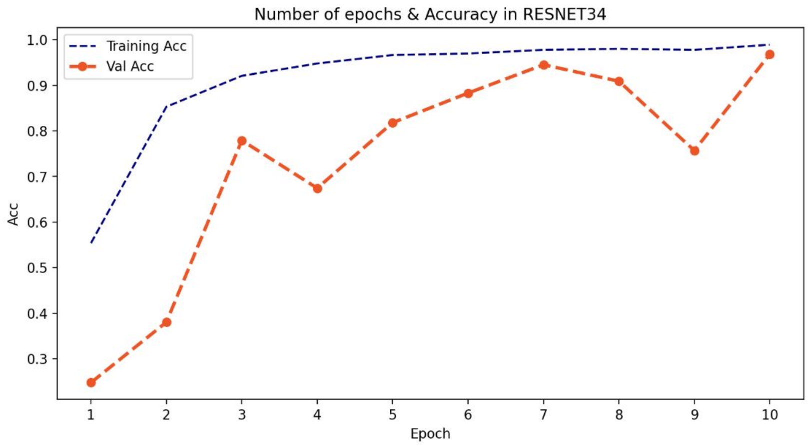
Training vs. Validation Accuracy:

- Training accuracy improved rapidly, reaching approximately 99% by the 10th epoch.
- Validation accuracy stabilized at 96%, demonstrating strong generalization.

Visual Insights:

- Loss and accuracy plots indicate effective learning with balanced performance between training and validation data.
- Minimal divergence between training and validation curves validates a well-tuned model.





Approach

AlexNet

- Built a custom AlexNet model for image classification with input dimensions of (240, 240, 3).
- Used convolutional layers with ReLU activation, batch normalization for stability, and MaxPooling for dimensionality reduction.
- Added dense layers with 2048 neurons and Dropout layers to prevent overfitting, optimizing efficiency by reducing neuron count.
- Configured the model with the Adam optimizer (learning rate = 0.001) and Binary Crossentropy loss, training it over 20 epochs.

Results

AlexNet

Training vs. Validation Loss:

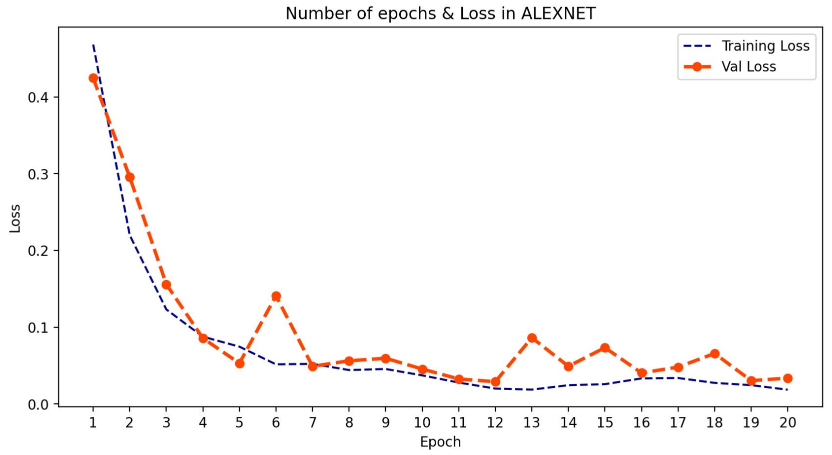
- Training loss decreased steadily, reaching close to 0.01 by the 20th epoch.
- Validation loss remained consistently low with minimal signs of overfitting, stabilizing around 0.02.

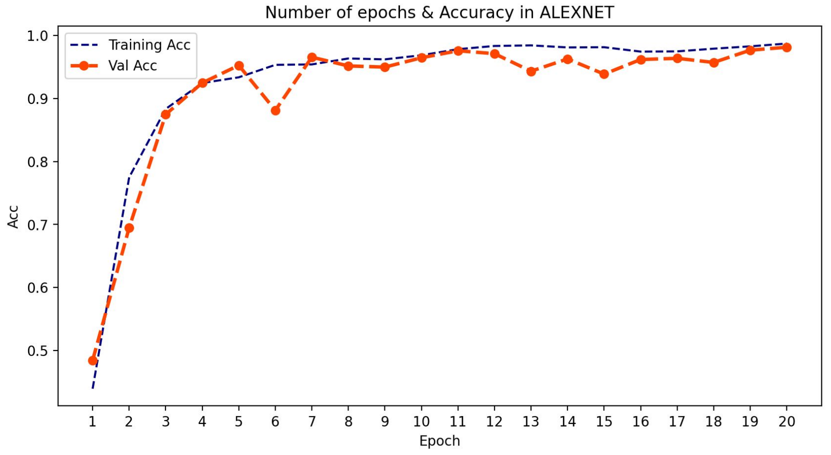
Training vs. Validation Accuracy:

- Training accuracy rapidly increased, reaching 98.8% by the final epoch.
- Validation accuracy closely followed, stabilizing at approximately 98.1%, indicating strong generalization.

Visual Insights:

- Loss curves confirm effective model learning, with minimal divergence between training and validation datasets.
- Accuracy curves illustrate consistent performance improvement and convergence over the epochs.





Approach

VGGNet

- Built a custom VGGNet with layers for convolution, batch normalization, max pooling, and dense layers for feature extraction and classification.
- Input size set to (240, 240, 3). Included dropout layers to mitigate overfitting and global average pooling for dimensionality reduction.
- Utilized Adam optimizer (learning rate = 0.001) and Binary Crossentropy as the loss function for multi-class classification.
- Trained the model over 10 epochs with data augmentation and a separate validation dataset for evaluation.

Results

VGGNet

Training vs. Validation Loss:

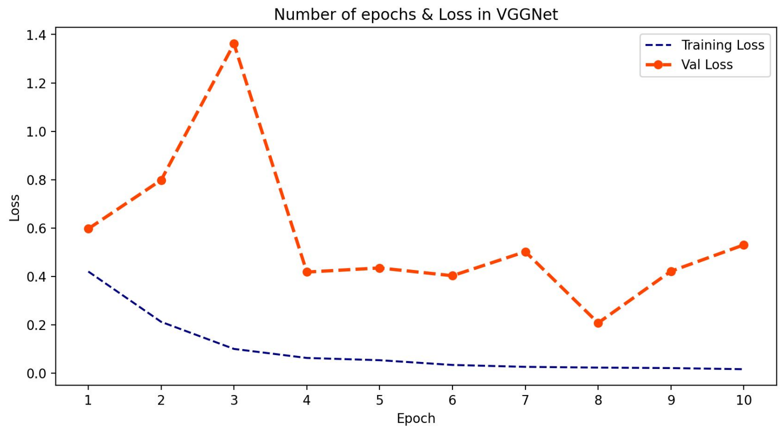
- Training loss steadily decreased, reaching near zero by the 10th epoch.
- Validation loss showed a decreasing trend but fluctuated in later epochs, indicating minor overfitting.

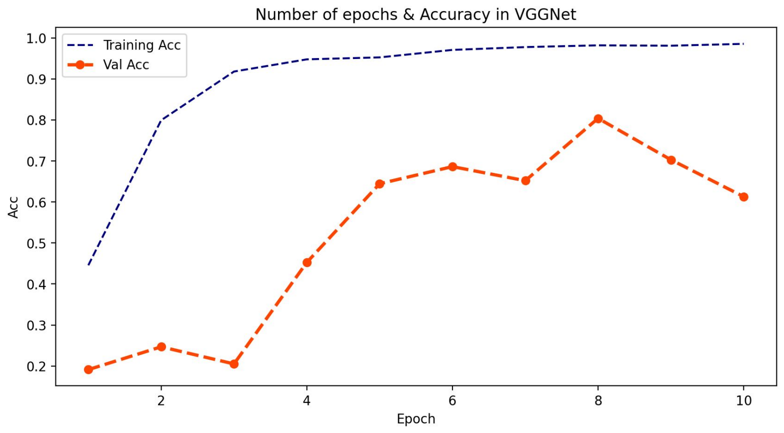
Training vs. Validation Accuracy:

- Training accuracy rapidly increased to 98%, demonstrating efficient learning.
- Validation accuracy peaked to 80% till the 8th epoch, later the model starting overfitting.

Visual Insights:

- Loss and accuracy curves highlight effective training but suggest potential improvements in regularization to address minor overfitting.





Conclusion

The performance comparison of AlexNet, ResNet34, and VGGNet for driver behavior detection revealed key differences:

- **AlexNet** achieved the best overall performance with a training accuracy of 98.81% and validation accuracy of 98.14%, demonstrating both robustness and generalization.
- **ResNet34** showed strong performance with a training accuracy of 98.46% and validation accuracy of 96.85%, indicating efficient training with slightly lower generalization compared to AlexNet.
- **VGGNet** had a comparable training accuracy of 98.47%, but its validation accuracy dropped significantly to 61.32%, suggesting overfitting and poor generalization.

Based on these results, **AlexNet** is the most reliable model for this task, balancing high training and validation accuracy. **ResNet34** is a close second, providing efficiency and generalization with fewer epochs. **VGGNet**, while strong during training, requires further tuning or adjustments to address overfitting issues.

Contributions & Implications

CONTRIBUTIONS

- This system can be used to detect dangerous driving behaviors in real-time.
- It could be integrated into Advanced Driver Assistance Systems (ADAS) for enhanced road safety.
- The system can warn drivers immediately to correct unsafe driving.

IMPLICATIONS

- Reducing accidents caused by distracted or unsafe driving.
- Potential applications in fleet management and autonomous vehicle systems.
- Insurance companies could adjust premiums based on driving behavior.

Challenges & Solutions

Multi-Class Classification: One of the challenges was effectively classifying different driver behaviors such as texting, talking, and safe driving.

Solution: We used a softmax activation function in the AlexNet model to improve the classification accuracy across multiple behavior categories.

Model Overfitting: During training, the model tended to overfit on the training data, which impacted its performance on unseen data.

Solution: To address overfitting, we applied dropout layers in both ResNet34 and VGGNet architectures, used batch normalization to stabilize training, and limited training epochs to prevent overfitting

Use Cases

Fleet Management: Companies can monitor driver behaviors in real-time to improve safety, optimize routes, and reduce accident risk in commercial fleets.

Autonomous Vehicles: This system acts as an additional safety layer in semi-autonomous vehicles, monitoring the human driver for distracted or unsafe behavior.

Insurance: Insurance providers can use this data to adjust premiums based on driver behavior, rewarding safe driving and encouraging better habits.

Public Safety: Government agencies or public transportation services can use the system to improve road safety in buses, taxis, and ride-sharing services.

Drive Safe!