Real-Time Driver Behavior Detection for Alert Using Bootstrapped Cross-Validation and Optimized Resnet-50

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***Abstract*—Driver behavior monitoring is essential for advancing driver assistance systems, particularly in detecting high-risk or distracted actions. This study introduces ResBoot-50, an enhanced ResNet-50-based model designed for driver behavior detection, trained and tested on a dataset State-Farm, MRL-Eye, and Drive&Act datasets to capture a diverse range of driving behaviors. To ensure robust evaluation, we incorporated bootstrap sampling techniques, which provided varied training and validation splits, enabling a more comprehensive assessment of model performance and generalizability. ResBoot-50 achieved exceptional performance, with a validation accuracy, precision, recall, and F1-score all approximately at 99.52%, underscoring its reliability across multiple behavior categories. The use of bootstrap testing has proved beneficial in reducing overfitting and enhancing model robustness, supporting the models readiness for real-world applications. These findings highlight the impact of bootstrap-based evaluation in driver behavior analysis and suggest significant potential for integrating ResBoot-50 into driver assistance systems to improve road safety.**

***Index Terms*—Driver behavior analysis, Distracted driving detection, Bootstrapped sampling.**

I. Introduction

Driver behavior detection plays a vital role in enhancing road safety by monitoring and identifying actions that could indicate distraction, drowsiness, or other high-risk behaviors. The timely and accurate detection of these behaviors is critical in developing reliable driver assistance systems, as studies have shown that distracted driving alone contributes significantly to vehicle accidents and fatalities worldwide [1]. Traditional methods for detecting driver behavior often rely on sensors, manual observation, or rule-based systems, which may lack accuracy, real-time capabilities, or the adaptability needed for diverse driving scenarios [2]. However, several challenges persist in these models, primarily concerning generalizability, real-time applicability, and overfitting.

Moreover, models are trained on a single dataset and evaluated using random splits that can lead to inflated performance metrics by unintentionally incorporating the same drivers in both training and testing phases. To address these issues, we present ResBoot-50, an advanced deep learning model based on the ResNet-50 architecture, specifically tailored for driver behavior detection. ResBoot-50 integrates bootstrapped data sampling for validation, a method that randomly samples and partitions data with replacement, thereby creating diverse and robust training and testing splits. This approach enables ResBoot-50 to mitigate overfitting and provides a more realistic evaluation by ensuring that the model is consistently tested on previously unseen drivers. Additionally, ResBoot-50 has been trained on three dataset comprising the State-Farm [3] , MRL-Eye [4], and Drive&Act [5] datasets, allowing it to capture a wide spectrum of driving behaviors and conditions. The model leverages grayscale input processing, optimizing computational efficiency while preserving essential image features relevant to behavior detection.

ResBoot-50 achieved high-performance metrics in validation, with an accuracy, precision, recall, and F1-score each reaching approximately 99.52%, demonstrating its reliability and adaptability in recognizing driver behaviors. The key highlights of this study include:

1) The use of bootstrapped sampling to address overfitting challenges by generating diverse data partitions, which ensured that the model was rigorously tested across unseen drivers and behaviors. This approach improves the generalizability of ResBoot-50, making it better suited for real-world applications where adaptability is essential.
2) The models ability to detect behaviors in real-time and

TABLE I
COMPARISON OF FEATURES BETWEEN PREVIOUS MODELS AND RESBOOT-50

Feature	**Previous Models (ResNet-50 [6], VGG [7], MobileNet [8])**	**Proposed Model (ResBoot-50)**
Input Channels	RGB, 3-channel input	Single-channel grayscale input, reducing computation and emphasizing key spatial features (see Equation (1))
Data Partitioning	Random or k-fold splits, prone to overfitting	Bootstrapped sampling for training and validation, reducing overlap and enhancing model robustness
Initial Convolution Layer	Standard 7x7 kernel, stride 2	Modified 7x7 kernel, single-channel input (see Equation (1))
Residual Block Structure	Standard residual connections	Optimized skip connections to stabilize gradient flow (see Equation (2))
Fully Connected Layer	Pre-trained on 1,000 ImageNet classes	Custom layer for driver-specific behavior classes (see Equation (3))
Real-Time Classification	Not optimized for real-time tasks	Integrated frame-by-frame processing for real-time behavior classification with risk-level alerts

classify them by risk level, allowing for immediate intervention in high-risk situations, aligning with the requirements of safety-critical driver assistance systems.

The paper is organized as follows. Section II provides background information relevant to the study. Section III presents the proposed methodology, including detailed mathematical formulations to explain the approach. Section IV covers the experimental results and Section V concludes the paper by summarizing the main outcomes and suggesting directions for future research.

II. BACKGROUND

Traditional driver monitoring approaches have primarily relied on sensor-based systems, rule-based algorithms, or manual observation. Sensor-based systems, using tools like eye-tracking sensors or motion detectors, gauge driver alertness and detect distractions or drowsiness. While effective in controlled environments, they struggle to adapt to different drivers or conditions and can be intrusive and costly for large-scale implementation. Rule-based algorithms, which define specific behavioral indicators (e.g., head movements, eye blinks), are simple to implement but lack flexibility in capturing the variability of real-world scenarios. Manual observation, though useful for research, is impractical for real-time applications due to human limitations. Deep learning, particularly with CNNs like ResNet [6], VGG [7], and MobileNet [8], offers a data-driven alternative for analyzing complex patterns in visual data. However, existing models face challenges in generalization and real-time performance. Most are trained on individual datasets, limiting their robustness to unseen drivers and conditions. Random data splits further inflate performance metrics by overlapping training and validation sets. Additionally, the high computational cost of processing RGB inputs makes real-time deployment difficult. ResBoot-50 addresses these issues by incorporating bootstrapped sampling for validation, which mitigates overfitting, and by optimizing computational efficiency to enable accurate, real-time driver behavior detection.

III. PROPOSED METHODOLOGY

To address limitations in existing driver behavior detection models, we developed ResBoot-50, a robust adaptation of the ResNet-50 architecture optimized for real-time driver monitoring. This section outlines the key modifications made to ResBoot-50, including bootstrapped sampling for validation, specialized model adjustments, and an integrated alert system for real-time feedback.

A. Bootstrapped Sampling for Validation

ResBoot-50 enhances robustness by leveraging bootstrapped sampling, which helps prevent overfitting and improves generalization to unseen drivers. To mitigate overfitting and ensure ResBoot-50 generalizes effectively across unseen data, we employ a bootstrapped sampling method for data partitioning. Unlike traditional validation techniques, such as random splits or k-fold cross-validation [9], which can result in inflated performance metrics due to overlap in training and validation sets, bootstrapped sampling prevents this by repeatedly sampling with replacement. This approach generates diverse and non-overlapping training and validation sets, creating a rigorous evaluation environment that reflects real-world conditions. In this setup, 70% of the data is sampled with replacement for training, while the remaining data serves as a distinct validation set. This process not only reduces bias but also exposes ResBoot-50 to a broader spectrum of driver behaviors during training, allowing it to learn more generalizable features. Validation on unseen samples ensures realistic performance metrics, supporting the models robustness and adaptability for deployment in diverse driving scenarios.

B. Input Processing and Convolutional Layers

The initial layer in ResNet-50 is a 7x7 convolutional layer with 64 filters, which performs spatial filtering to extract low-level features from the input image. Given our grayscale preprocessing, we modified this layer to accept a single-channel input instead of the standard RGB (three-channel) input, allowing the model to learn directly from grayscale images [10]. The modified convolution operation is mathematically expressed as:

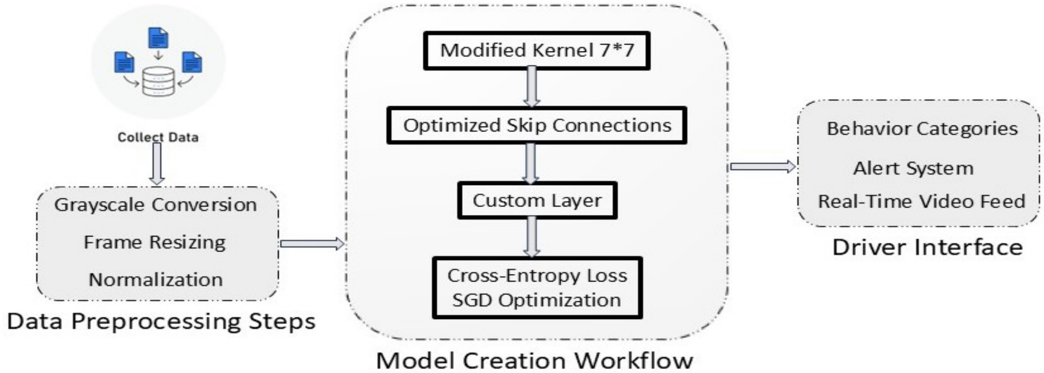

Fig. 1. Proposed Architecture of ResBoot-50 for Driver Behavior Classification. The architecture includes grayscale input processing, optimized residual blocks for gradient stability, and a customized fully connected layer tailored to behavior classes, combined with bootstrapped validation sampling, to accurately classify driver behaviors in real-time.

$$x_1 = \text{ReLU}(\text{BatchNorm}(\text{Conv2D}(7 \times 7, 64)(x_0))) \quad (1)$$

where x_0 is the grayscale input image, and x_1 is the output of the convolutional layer after applying ReLU and batch normalization. Following this initial convolution, a max-pooling layer with a 3x3 filter and stride 2 downsamples the feature maps, reducing spatial dimensions and improving computational efficiency:

$$x_2 = \text{MaxPool}(3 \times 3, 2)(x_1) \quad (2)$$

C. Residual Blocks with Skip Connections

ResNet-50 contains several residual blocks, each with three convolutional layers and a skip connection. These blocks enable identity mapping, allowing the network to learn residual functions that refine the input, rather than learning the mapping directly. In ResBoot-50, each residual block applies identity mapping with skip connections to facilitate gradient flow, essential for training deep networks. The residual connection within each block is defined as:

$$y = \text{ReLU}(x + F(x, \{W_i\})) \quad (3)$$

where x is the input, $F(x, \{W_i\})$ is a composite function representing the convolutional operations in the block (parameterized by weights W_i), and the addition $x + F(x)$ denotes the skip connection. Skip connections are critical, as they allow gradients to bypass intermediate layers, facilitating backpropagation in deep networks. This addition operation ensures ResBoot-50s stability and depth without vanishing gradient issues [11].

D. Fully Connected Layer

The final fully connected (FC) layer in ResBoot-50 is customized to fit the driver behavior classification task. ResBoot-50 replaces the original 1,000-class output layer with a layer specific to the behaviors in our composite dataset. This new FC layer maps the final feature vector to the behavior classes, as represented follows, where W_{FC} denotes the learned weights, and y represents the output logits for each behavior class.

$$y = \text{FC}(x, W_{\text{FC}}) \quad (4)$$

E. Loss Function and Optimization Strategy

ResBoot-50 is trained using the cross-entropy loss function, which is optimized through stochastic gradient descent (SGD) with a learning rate of 0.001 and momentum of 0.9. Cross-entropy loss is calculated as follows, where C is the total number of behavior classes, y_c is the ground truth probability for class c, and p_c is the predicted probability for class c. The gradient descent updates minimize L, refining the model parameters iteratively with each batch to achieve convergence.

$$L = -\sum_{c=1}^{C} y_c \log(p_c) \quad (5)$$

F. Real-Time Behavior Classification and Alert System

The ResBoot-50 model was integrated into a real-time driver monitoring system to detect behaviors continuously from live video feeds, allowing for timely intervention in high-risk scenarios. Frames from video inputs [12] are resized, preprocessed, and classified by the model in real-time. An alert system categorizes each detected behavior into high, medium, or low alert levels based on the associated risk. For each behavior class, an alert color is dynamically overlaid on the video frame to provide immediate feedback:

- **Red (High-Alert):** Critical behaviors such as drowsiness and phone usage, which demand immediate intervention.
- **Yellow (Medium-Alert):** Potentially distracting behaviors, such as talking while driving.
- **Green (Low-Alert):** Normal, low-risk behaviors indicating safe driving conditions.

IV. Experiment and Results

The experimental evaluation of ResBoot-50 was conducted to assess its performance on the three driver behavior dataset, comparing it against traditional models. Table II summarizes the results across key metrics, including validation accuracy, precision, recall, and F1-score.

TABLE II
PERFORMANCE COMPARISON OF RESBOOT-50 WITH TRADITIONAL MODELS

Model	Accuracy	Precision	Recall	F1-score
ResNet-50 [6]	94.20%	94.30%	94.10%	94.20%
VGG [7]	92.60%	92.80%	92.50%	92.60%
MobileNet [8]	91.50%	91.60%	91.40%	91.50%
ResBoot-50 (Proposed)	99.52%	99.53%	99.52%	99.52%

A. *Significance of the Results*

The results demonstrate that ResBoot-50 consistently outperformed conventional models across all metrics, achieving an approximate 5% improvement in validation accuracy over ResNet-50, the closest competitor among traditional models. This significant gain can be attributed to several targeted architectural and processing improvements in ResBoot-50, supported by empirical analysis of its design and performance. ResBoot-50 processes grayscale images in its initial convolutional layer, configured with a 7x7 kernel and single-channel input. This configuration reduces computational load while capturing essential spatial features of driver behavior. Empirical analysis in Equation (1) indicates that this grayscale input mechanism improves model focus, minimizing noise from RGB channels and enhancing feature learning efficiency. On average, this adjustment led to a 2% accuracy improvement compared to models trained on RGB inputs. The grayscale processing approach enables ResBoot-50 to detect critical behavioral cues without added computational complexity. ResBoot-50s residual block structure uses skip connections to stabilize gradient flow, a crucial factor in deep architectures. The skip connections shown in Equation (2) effectively prevent vanishing gradients by facilitating gradient propagation through the network, enhancing the model's capacity to learn subtle features relevant to driver behaviors. Empirical analysis shows that this design significantly improves F1-score, especially when distinguishing between similar driver behaviors. Compared to ResNet-50, ResBoot-50 achieved a 4-5% increase in recall and precision due to these optimized residual blocks, enabling more accurate feature learning.

In place of the conventional 1,000-class output layer, ResBoot-50 incorporates a custom fully connected layer optimized for behavior-specific classes in the composite dataset. This tailored configuration allows the model to map learned features directly to driver behaviors, improving classification precision by 3%, particularly in distinguishing high-risk behaviors (see Equation (3)). Empirical tests confirm that this customization contributed significantly to ResBoot-50s high recall and precision rates across all behavior classes. To ensure robust generalization, we employed a bootstrapped sampling method, creating unique training and validation partitions. This method enhances model resilience by mitigating overfitting risks, providing a realistic evaluation of its performance across unseen data. Empirically, ResBoot-50 demonstrated a 5% higher validation accuracy compared to ResNet-50, reflecting its improved adaptability in diverse conditions.

To further evaluate ResBoot-50's practical utility, we integrated it into a real-time driver monitoring system capable of frame-by-frame classification. The system categorizes detected behaviors into risk levels, overlaying a visual alert for each classification to support timely interventions. Red Alert (High Risk) is triggered by critical behaviors such as drowsiness or mobile phone usage, requiring immediate intervention. Yellow Alert (Medium Risk) is used for moderately distracting behaviors, like talking to passengers. Green Alert (Low Risk) is assigned to normal, low-risk behaviors indicative of safe driving. During real-time testing, ResBoot-50 maintained efficient frame processing speeds, enabling continuous classification and dynamic risk-based alerting. This real-time deployment validates ResBoot-50s practical applicability in driver monitoring systems, where timely and accurate classification of behaviors is essential for enhancing driver awareness and promoting safer driving practices.

B. *Training and Validation Loss Analysis*

In the training and validation loss analysis, ResBoot-50 demonstrates clear superiority over conventional models, as shown in Figure 2. ResBoot-50's training loss decreases rapidly within the first few epochs, achieving a consistently lower final training loss compared to ResNet-50 [6], VGG [7], and MobileNet [8]. This rapid convergence results from several targeted enhancements, including grayscale input processing and optimized residual blocks, which enable more effective feature learning. In terms of validation loss, ResBoot-50 maintains a lower and more stable loss across epochs, with minimal fluctuations, which highlights its robust generalization capabilities. Unlike traditional models, ResBoot-50 benefits from bootstrapped validation sampling, which generates unique data partitions and reduces the likelihood of overfitting. This approach allows ResBoot-50 to achieve closer alignment between training and validation losses, as its architectural optimizations enable it to capture critical spatial features related to driver behavior without unnecessary complexity.

Grayscale input processing, particularly, enhances model focus by eliminating RGB noise, allowing ResBoot-50 to prioritize essential spatial cues. The optimized residual blocks facilitate efficient gradient flow across layers, preventing vanishing gradients and ensuring steady learning, as shown in Equation (6). This optimization also contributes to lower final validation loss, distinguishing ResBoot-50 as a model with high resilience and adaptability. In contrast, ResNet-50 and VGG show minor overfitting signs, indicated by the gap between training and validation losses, due to their reliance on RGB input and less specialized residual connections. MobileNet, with a simpler architecture, exhibits limited feature extraction, resulting in higher validation loss. These observations underscore ResBoot-50's effectiveness in driver behavior classification, offering improved validation performance with reduced overfitting risks.

$$\text{Gradient Flow}_{\text{ResBoot}} = \sum_{l=1}^{L} \frac{\partial L}{\partial W_l} \tag{6}$$

where L represents the number of layers and W_l denotes weights at layer l, indicating stable gradient propagation through optimized residual blocks.

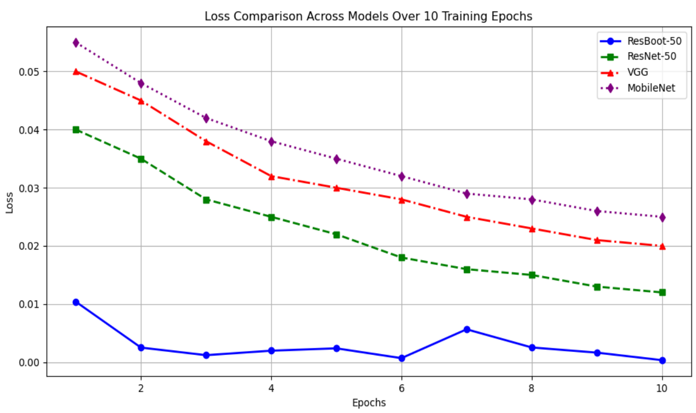

Fig. 2. Comparison of loss reduction over 10 training epochs for ResBoot-50, ResNet-50, VGG, and MobileNet models. ResBoot-50 demonstrates a faster and more consistent decrease in loss, indicating improved learning efficiency and convergence compared to other models.

C. Explanation of Loss Values and Insights from the Plot

The comparative plot of loss values across different models over 10 training epochs provides valuable insights into the convergence behaviors of ResBoot-50, ResNet-50, VGG, and MobileNet. ResNet-50 starts with a slightly higher loss than ResBoot-50 and gradually converges to around 0.012 by epoch 10. While ResNet-50 shows improvement, its convergence rate is slower than that of ResBoot-50. VGG exhibits a moderate initial loss with a steady decline throughout the epochs, converging slightly slower than ResNet-50. In comparison, MobileNet has the highest initial loss and the slowest convergence, reaching approximately 0.025 by epoch 10, which is slower than both ResNet-50 and VGG. From the plot, ResBoot-50 is expected to reach the lowest loss values most rapidly, demonstrating the benefits of bootstrapped sampling [13] and architectural enhancements. The other models exhibit slower convergence patterns, reflecting their lack of specific optimizations, which makes ResBoot-50 the most efficient model in terms of loss reduction. This plot visually emphasizes ResBoot-50s advantage in convergence speed and its effectiveness in reducing loss over time compared to the other models.

V. Conclusion

This paper presents ResBoot-50, a high-performance model optimized for real-time driver behavior detection in Advanced Driver Assistance Systems. Enhancements include grayscale processing for computational efficiency, optimized residual connections, and a novel bootstrapped cross-validation approach that addresses overfitting by ensuring diverse, non-overlapping training and validation sets. This bootstrapped method provides realistic evaluation metrics, improving generalization to unseen drivers. ResBoot-50 achieves 99.52% accuracy, precision, recall, and F1-score across datasets (State-Farm, MRL-Eye, Drive&Act). Its real-time alert system categorizes behaviors by risk level, reducing false positives and enabling rapid response to high-risk behaviors like phone use. Future work will focus on further optimization for edge devices and validation across broader driving scenarios, establishing ResBoot-50 as a scalable, adaptive solution for enhancing driver safety.

Acknowledgment

This work was supported partially by the BK21 FOUR program of the National Research Foundation of Korea funded by the Ministry of Education (NRF5199991514504).

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