To Design and Train a Model that Can Detect Distracted Driver Behaviour, Identifying Common Distractions such as Phone Usage, Eating and Other Inattentive Actions

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ABSTRACT
Distracted driving is a significant contributor to road accidents globally, often resulting from activities such as texting, eating, or interacting with devices while operating a vehicle. This study proposes a robust machine learning-based approach to detect and classify distracted driver behaviors using visual data. Leveraging the State Farm Distracted Driver Detection dataset, the system begins by preprocessing image data categorized into distinct distraction classes. A Convolutional Neural Network (CNN) is implemented for automatic feature extraction, effectively capturing spatial hierarchies from driver images. To enhance efficiency and reduce feature space complexity, Principal Component Analysis (PCA) is applied, reducing the extracted 128-dimensional feature vectors to 16 components. The reduced features are then classified using a Support Vector Machine (SVM) classifier, evaluated both with and without PCA to compare performance. Evaluation metrics such as confusion matrix, classification report, and AUC are used to validate the model. The findings reveal that the combined CNN-PCA-SVM pipeline delivers strong classification accuracy and reliability, suggesting its potential integration in real-time driver monitoring systems to improve road safety.

Keywords: Distracted Driving; Convolutional Neural Networks (CNN); Principal Component Analysis (PCA); Support Vector Machine (SVM); Driver Behavior Detection; Image Classification; Deep Learning; Computer Vision; Road Safety; Driver Monitoring System

1. INTRODUCTION

By taking a driver's focus away from the task of driving, distracted driving jeopardizes road safety. Numerous devices that divert a driver's attention include phones, infotainment screens, navigation systems, and commonplace technologies. The pervasiveness of this problem is acknowledged in several national publications, highlighting its applicability to all traffic safety analyses.

In 2022, the Indian Ministry of Road Transport and Highways (MoRTH) recorded around 461,312 road accidents. Approximately 25% of all recorded accidents, injuries, and fatalities were caused by driver distraction-related incidents like "Hit from Back" and "Run Off-Road" Similar patterns can be seen in European data. According to roadside observations conducted by the European Road Safety Observatory (ERSO), handheld phone use while driving ranged from 1.7% to 9.4% in all member states. Conversely, self-reported phone use ranged from 13% to 53% for texting and 12% to 59% for calls.

However, there are a number of technological difficulties in incorporating such automated procedures into a conventional transportation system. Automated systems must have a thorough awareness of their environment since host or remote vehicle drivers are stochastically distributed. Furthermore, such systems need to be created within a flexible framework that considers driver behavior models in order to increase their performance and efficiency**(Mangal, B., Bhatia, A., Sharma, Y., Tiwari, K., & Verma, 2025).**

To guarantee the safety of future transportation, the broad use of self-driving vehicles (SVs) requires legal driving1. In addition to providing important evidence for the traceability of traffic incidents, independent online monitoring of SVs' driving behavior is crucial for government regulation of autonomous driving. It can also alert autonomous driving algorithms to infractions, thereby enhancing their adherence to regulations. These days, human-oriented traffic laws have many vague terms that businesses interpret differently, which results in different actions from self-driving car (SV) systems.

1.1 Role of Deep Learning in Intelligent Transportation Systems

In the rapidly evolving world of modern transportation, Intelligent Transportation Systems (ITSs) have become a transformative force that is radically altering the way that people and goods are transported. In order to increase the efficiency, security, and environmental friendliness of transportation networks, they integrate state-of-the-art technology, data analytics, and communication systems.

Modern information and communication technology is used by ITS to improve public transportation networks, vehicle operation, and traffic management, among other aspects of transportation. ITS uses real-time data, sensor networks, and cognitive algorithms to reduce traffic congestion, shorten travel times, increase safety, and minimize environmental effects(**Elassy, M., Al-Hattab, M., Takruri, M., & Badawi, 2024)**.

1.2 Importance of Monitoring Driver Behavior
The development of autonomous or self-driving cars—vehicles that can function without human assistance—has received more attention lately. This advancement has made it possible to improve these cars' safety in new ways. The ability to comprehend and monitor what is happening within the car, especially with the driver, is a crucial component. Driver inattention has been thoroughly examined by researchers, who have divided it into two main categories: visual distraction and weariness. A comprehensive strategy is needed to identify and address driver inattention, including subjective reports, physical measurements, biological indicators of the driver, driving performance evaluations, and hybrid measures that integrate several signs. In particular, hybrid measures provide more precise and dependable answers than depending only on one measure. Commercial driver inattention monitoring devices do exist, nevertheless, and their usefulness under real-world driving circumstances might be restricted. In order to improve safety, the best driver inattention monitoring system incorporates driving performance measures, driver physical characteristics, and information from the In-Vehicle Information System (IVIS) while taking the driving environment into account**(Qu, F., Dang, N., Furht, B., & Nojoumian, 2024).**

1.3 Classical Machine Learning vs. Deep Learning for Driver Detection
Because deep learning models, such as Convolutional Neural Networks (CNNs), can extract complicated information from images, they are frequently utilized in driver behavior detection. However, their usage in real-time or low-resource situations is limited since they frequently call for huge datasets, considerable processing power, and additional training time**(Jami, A., Razzaghpour, M., Alnuweiri, H., & Fallah, 2024).**
However, when combined with dimensionality reduction strategies like Principal Component Analysis (PCA), traditional machine learning models like Support Vector Machines (SVM) provide a more effective option. By reducing visual data into a lower-dimensional space, PCA helps the SVM classify various driving behaviors more quickly and with less memory usage. This combination offers a lightweight and efficient solution that is particularly appropriate for real-world applications where simplicity and speed are crucial**(Wu, J., Huang, C., Huang, H., Lv, C., Wang, Y., & Wang, 2024).**

2. LITERATURE REVIEW:
Abolfazl Taherpour et al (2024) Using a phone while driving is frequently cited as one of the main contributing factors to distracted driving. Similar to this, voice messaging has been mentioned in the literature as a possible contributing factor to distracted driving, but it hasn't gotten much attention. Therefore, the goal of this research is to leverage vehicle trajectory data to build supervised machine learning (ML) techniques for detecting distracted driving incidents brought on by texting and voice messaging. 92 individuals used a driving simulator to drive a simulated network of the Baltimore metropolitan region, and vehicle trajectory data was gathered from them. To build the features for the ML approaches, several important variables were taken out of the data, such as speed, brake usage, throttle, steering velocity, brake light, and deviation from the road center.

M Bergström et al (2024) For both inexperienced and seasoned drivers, driving distraction is one of the main factors contributing to traffic fatalities and accidents. As a result, laws have begun to focus on the creation and application of measures to identify and stop this type of conduct, which is referred to as secondary tasks when driving. Particularly risky are some auxiliary tasks, like texting. In order for the automobile system to successfully help the driver reduce such behavior, research and development is underway for driver monitoring systems. The most popular method of tracking human activity is to utilize cameras to record video streams that are then fed into machine learning models that are trained to recognize and identify various actions. This paper's scope includes defining phone usage in relation to driving, gathering data in a simulator, preprocessing the data, and training machine learning models to forecast driver behavior.

M Rifai et. All (2020) As the number of cars on the road continues to climb, traffic congestion and the risk of accidents both worsen. Ignoring a red light is a significant infraction that usually results in collisions. Due to the rapid distribution of green time on comparatively crowded lines, drivers may be more likely to ignore the signals. To track traffic signal compliance and spot violations, like vehicles failing to stop at a zebra crossing when the light is red, this capstone project uses a convolutional neural network technique. The sensor in this case is the camera. Three cameras are used in each row. The microcontroller will get the number of cars detected from the laptop. Data on the number of cars waiting at the light is sent into a convolutional neural network to calculate how long the green light should last. The infraction will be noted if the car stops past the stop line while the red light is on.

Arian Shajari et al (2023) Acknowledging the diverse distractions impacting drivers and their performance, this paper conducts a comprehensive review of existing studies in the realm of driver distraction detection. The examination involves the identification and elucidation of various variables inherent in current methodologies and experimental setups. The findings of these experiments, encompassing the effects of distinct distraction factors on drivers' physiological responses, visual signals, and overall performance, are systematically categorized and expounded upon. Additionally, the study critically analyzes the methodologies and results of extant research, shedding light on inherent factors and discerning research gaps.

Y. Albadawi et al (2022) In the past decade, significant strides in computing technology and artificial intelligence have propelled advancements in driver monitoring systems. This paper offers a comprehensive review of driver drowsiness detection systems developed during this period, showcasing diverse experimental studies that leverage real driver drowsiness data and employ various artificial intelligence algorithms. Categorizing these systems based on the information utilized, the paper provides detailed insights into their features, classification algorithms, and datasets. Evaluation metrics such as classification accuracy, sensitivity, and precision are scrutinized, shedding light on the effectiveness of these systems. The paper also addresses recent challenges, assesses the practicality and reliability of different system types, and outlines future trends in the dynamic field of driver drowsiness detection.

3. METHODOLOGY

The methodology adopted in this study involves the design implementation and evaluation of deep learning models for Distracted Driver behavior detection using image data. This research follows a multi-stage pipeline comprising data collection, Data preprocessing, Model architecture, Model training and evaluation.

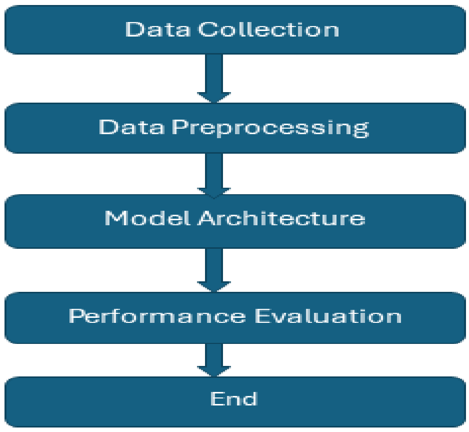

Figure 3.1 Workflow of Distracted Driver Behavior Detection System

3.1 Dataset

The State Farm Distracted Driver Detection dataset includes more than 22,000 tagged photos of drivers engaging in 10 different kinds of behavior (such as texting, eating, using a phone, and safe driving). To comply with CNN input specifications, photos are scaled to 224×224 pixels and each behavior is grouped into folders c0 through c9.

3.2 Data Preprocessing

To guarantee consistency, lower complexity, and boost performance, the image data underwent a number of preparation and transformation stages prior to model training:

- **Image resizing:** OpenCV was used to resize each image to a predetermined size of 100 × 100 pixels.
- **Normalization:** By dividing by 255, pixel values that were initially between 0 and 255 were scaled to a [0, 1] range.
- **Label Encoding:** Driver behavior characteristics, such as safe driving, texting, chatting on the phone, etc., are mapped to class labels ranging from c0 to c9.
- **Flattening:** To be used as input for PCA, images were flattened from 2D (100×100×3) to 1D vectors (30,000 features per image).
- **Dimensionality Reduction:** In order to reduce computational complexity and preserve important properties, dimensionality reduction was carried out.
- **Train-Test Split:** the ratio of the training and testing data is 80:20.

3.3 Model Architecture

The suggested model for detecting inattentive drivers uses a hybrid architecture that blends traditional machine learning classifiers for final decision-making with deep learning-based feature extraction.

CNN Model

A custom Convolutional Neural Network (CNN) was constructed using the Tensorflow/keras framework and this architecture include:

- **Dropout layers**: used to prevent overfitting.
- **Output Layer:** The final output layer uses softmax activation to classify the input into one of the 10 behavior categories (multi-class classification).
- **Dense Layer:** Dense layer are used to combine extracted features and interrupted high-level pattern.

- **MaxPooling:** for hierarchal feature extraction

Principal Component Analysis (PCA)
After extracting deep features from the CNN, **Principal Component Analysis (PCA)** was applied:
- **Input to PCA**: Feature vectors extracted from the CNN.
- **Reduced Dimensions**: 16 principal components were retained.
- This step significantly reduced the complexity while preserving important feature variance.

K-Nearest Neighbors:
- uses the majority label of its closest neighbors to classify a test image.
- To determine the ideal value of k, hyperparameter tuning was done.

Support vector machine:
- A linear SVM classifier was trained using the PCA-reduced feature vectors, and it performed exceptionally well when dealing with high-dimensional input fields.

3.4 Performance Evaluation
- **Area Under the Curve**: The classifiers' capacity to differentiate between several classes is evaluated using the AUC (Area Under the Curve).
- **Accuracy**: Overall classification performance.
- **Classification Report**: Includes precision, recall, F1-score

4. RESULT AND ANALYSIS
4.1 Class Distribution
A bar chart was used to visualize the number of samples available in each class.
The dataset contains a balanced number of images for each class (C0 to C9).
This balance ensures that the models will not be biased towards for any one class.

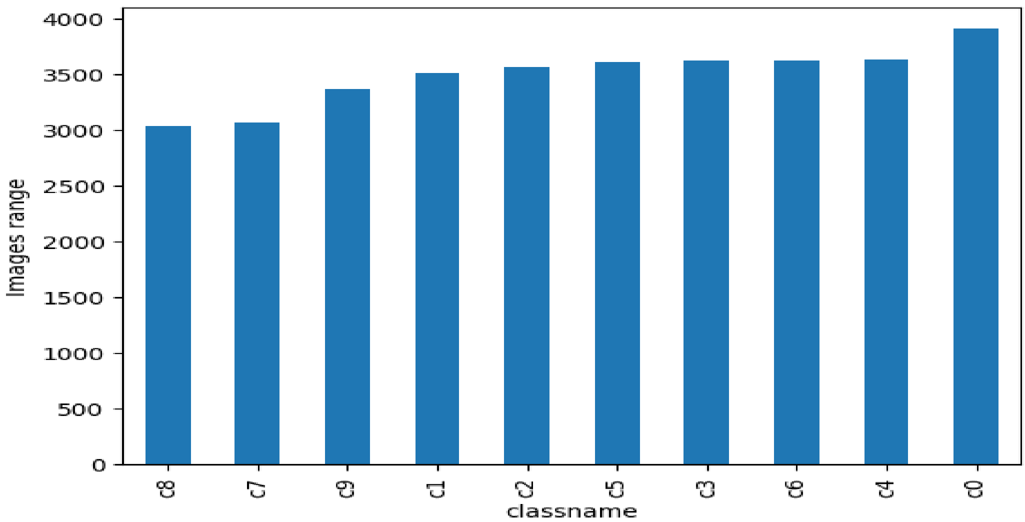

Figure4.1: Class Distribution of each class

4.2 Random Samples of Driver Behavior Classes
A selection of randomly selected training set photographs that show a range of driver behaviors in various subjects and situations are shown in the image below. It provides a visual representation of the dataset's intra- and inter-class variation.

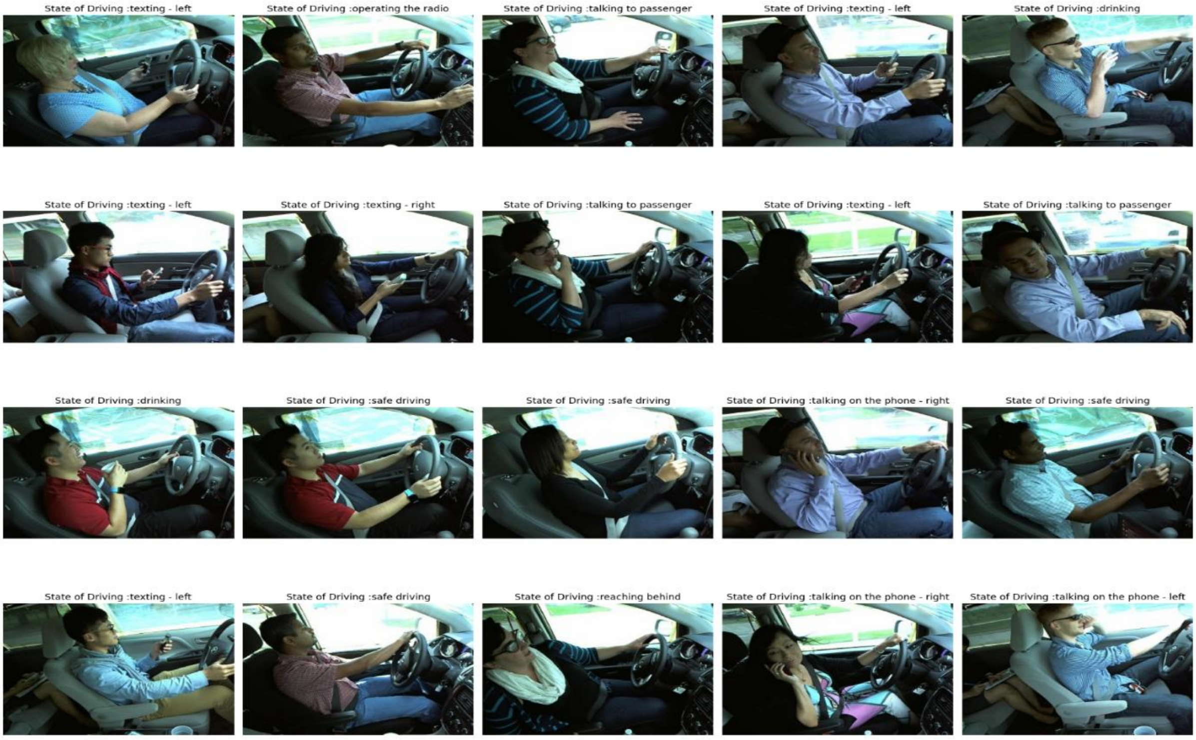

Figure 4.2: Driver Behaviors for each class

4.3 Performance Comparison of Classification Models

Accuracy, precision, recall, and F1-score are common classification metrics that were used to test several models, including CNN, SVM, KNN, and Random Forest, in order to determine how well they detected distracted driving behavior. To guarantee equity across all courses, the outcomes were assessed using a balanced test set.

Table1: Performance Comparison of Different Models

Model	Accuracy	Precision	Recall	F1-Score
CNN	92.00%	0.92	0.92	0.92
SVM	99.00%	0.99	0.99	0.99
KNN	99.00%	0.99	0.99	0.99
Random Forest	99.00%	0.99	0.99	0.99

The accompanying table presents a comprehensive comparison of various machine learning and deep learning models used for distracted driver behavior classification. Based on the findings:

- CNN attained an accuracy of 92%, making it a solid deep learning baseline. It performed well but somewhat behind typical ML models.
- SVM, KNN, and Random Forest all gave great performance with 99% accuracy, precision, recall, and F1-score, suggesting superior ability to discern between distinct driving behaviors.
- Despite equal scores, Random Forest and KNN may offer superior interpretability and faster training than CNN.
- These findings suggest that conventional ML models, when paired with adequate feature extraction and preprocessing, can match or beat CNNs on structured datasets.

5. CONCLUSION:

Using both deep learning and traditional machine learning methods, a thorough and multi-phase framework was created in this study for the identification and categorization of distracted driving behavior. Images from 10 different driver behavior classifications, including frequent distractions like texting, using a phone, and engaging with in-car objects, made up the dataset. The ability of a bespoke Convolutional Neural Network (CNN) to learn spatial hierarchies directly from raw visual data was demonstrated when it was used for automatic feature extraction. It obtained a respectable accuracy of 92%. However, traditional classifiers like Support Vector Machine (SVM), K-Nearest Neighbors (KNN), and Random Forest demonstrated exceptional performance after applying dimensionality reduction through Principal Component Analysis (PCA). They achieved an impressive 99% accuracy along with nearly perfect precision, recall, and F1-scores
.

These findings demonstrate that, in structured picture classification tasks, traditional machine learning models can not only compete with deep learning techniques but also, in certain situations, outperform them with proper preprocessing and feature transformation. Furthermore, classical models are especially appealing for real-time or resource-constrained applications, including in-vehicle driver monitoring systems, due to their simplicity, interpretability, and lower processing requirements. However, CNNs are still very promising for unstructured or large-scale data settings, and they may perform better than classical models if they are trained using larger datasets, deeper architectures, or transfer learning from pretrained models.

Overall, this study's results highlight how crucial it is to choose models according to deployment restrictions, dataset properties, and task difficulty. The comparative performance analysis demonstrates that hybrid techniques, in which traditional machine learning is utilized for classification and deep learning is employed for feature extraction, can provide a potent balance between efficiency and accuracy. This study offers a feasible method for incorporating distracted driver detection systems into practical safety technologies and establishes a strong basis for future research in intelligent transportation systems.

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