Autonomous IoT Enabled Hazard detection and Communication System for Deaf Drivers.

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Declaration of the Candidate & the Supervisor.

Declaration

We declare that this is our own work, and this proposal does not incorporate without acknowledgement any material previously submitted for a degree or diploma in any other university or Institute of higher learning and to the best of our knowledge and belief it does not contain any material previously published or written by another person except where the acknowledgement is made in the text.

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The above candidates are carrying out research for the undergraduate Dissertation under my supervision.

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22/08/2024
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Abstract

In this technological era the automobile industry has undergone a significant improvement in road safety with many of the developments being driven by machines rater than humans. In resent years these advancements have given the vehicles the ability to see and hear using Computer Vision and Artificial Intelligence (AI). These technologies have enabled vehicles the ability to detect hazards, prevent accidents and ensure the overall safety of the drivers. Despite these achievements, deaf drivers continue to face unique challenges on the road specially when as perceiving auditory cues such as emergency vehicle sirens, horn sounds and verbal communications between pedestrians and fellow drivers.

Although most modern vehicles are equipped with these advanced safety systems, those are unable to fulfill the unique needs of a deaf driver due to those systems are mainly designed with the assumption that drivers can hear and respond to auditory alerts. This assumption creates a significant gap in safety for deaf drivers, as they may not receive the necessary warnings or communications in time to prevent an accident. This lack of reliable method of communication at critical moments makes it even more difficult for deaf drivers to react appropriately to potential hazards, putting their safety and the safety of others at risk.

To address this technological gap, this study is proposed the development of an Autonomous IoT-Enabled Hazard Detection and Communication System specifically designed for deaf drivers. By utilizing multiple sensory modalities and AI and Machine Learning (ML) technologies, this system aims to significantly improve both the safety and driving experience of deaf drivers. Ultimately, this research seeks to create a safer and more inclusive driving environment, ensuring that all drivers, regardless of their hearing ability, have access to the tools and information they need to navigate the roads safely.

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Introduction

Background

Since the invention of automobiles in 1904 those machines have been the taken over the world as the primary transportation method. But with the rapid development of technology modern automobiles have become a crucial part of human life. From entertainment to warfare automobiles are used in many different fields. Driving and maintaining these machines have become its own industry creating its own specialties which requires various skills.

In recent years, integrated with technologies like Artificial Intelligence (AI) and Internet of Thongs (IoT) automobiles have given the ability of vision and hearing. These innovations significantly enhance the safety of the drivers, passengers and pedestrians making the vehicle smart, responsive and autonomous. Modern automobiles now have the ability to detect hazards, prevent collisions and even communicate with other vehicles to optimize the traffic flow. Despite these advancements there is a crucial technological gap between how these advances addresses to all the drivers specially drivers with hearing impairments.

Approximately 466 million people worldwide, or over 5% of the world's population are identified as deaf or hard of hearing (DHH) [1]. In the streets deaf drivers face unique challenges mostly due to their inability to perceive auditory cues such as vehicle horn sounds, emergency vehicle sirens and verbal communication attempts from fellow drivers/ pedestrians. These cues are crucial for timely responses to emergency situations such as responding to the honk of a near by vehicle or providing road space for an emergency vehicle to pass. The current solutions for providing road safety, while effective for the general population, those systems cannot cater the special needs of the deaf driver who rely more heavily on visual information. There for deaf drivers could miss crucial alerts from traditional systems making them unable to respond in time increasing the risk of an accident.

In response to the growing need for specialized systems that can close the communication gap and provide deaf drivers with the necessary tools to navigate the roads safely this research is purposed on an Autonomous IoT-Enabled Hazard Detection and Communication System specifically designed for deaf drivers. The main goal of the purposed system will be to provide real time visual and haptic alerts, ensuring the deaf driver receives the information in time and respond correctly to the road hazards. The purposed research sets the stage to development of an innovative solution that uses AI, IoT, mobile applications and advanced sensor technologies to create safer driving experience for deaf drivers. By addressing the unique needs of deaf drivers, these systems can help ensure that all road users have equal access to the benefits of modern vehicle safety technologies, ultimately contributing to a safer and more inclusive transportation ecosystem.

The purposed system will utilize a combination of sensors to detect road hazards approaching emergency vehicles, continuous honking of other vehicles and other verbal communications. When detected the system can alert the driver by visual cues on the drivers' smart phone as well as through haptic feedback in the steering wheel. These alerts are to be designed in a way that the deaf driver can notice immediately and respond without delay.

In addition to hazard detection this system features a driver behavior monitoring system to analyze the drivers' behavior toward the hazard detection system. This system monitors the drivers' attitude towards the hazard detection system and the way the driver responds to the notified hazards. Mainly the system monitors how much attention the driver pays to the hazard detection system and whether the driver make correct and timely responses to the notified hazards.

In addition, the purposed system will also include features to enable deaf drivers to communicate and interact with other drivers, passengers and emergency services. The systems' integrated mobile application allows the user/ deaf driver to send per – set massages to the emergency services informing them in case of an emergency.

By utilizing multiple sensory modalities and cutting-edge technology, this system aims to significantly improve both the safety and independence of deaf drivers. Ultimately, this research seeks to create a safer and more inclusive driving environment, ensuring that all drivers, regardless of their hearing ability, have access to the tools and information they need to navigate the roads safely.

Literature Review

Driver Behavior Monitoring and Reporting System

In this section existing solutions for Driver Behavior Monitoring will be considered. This discussion will reveal the methodologies used by previous researches and how the driver behavior monitoring has evolved over time.

A research [1] conducted by Atif Alamri, Abdu Gumaei, Mabrook Al-Rakhami, Mohammad Mehedi Hassan, Musaed Alhussein and Giancarlo Fortino suggests a system designed to detect dangerous driver behavior such as high acceleration, sudden braking, sudden lane changes etc. The system architecture purposed by the researchers have three main components, the detection module, the training and validation module and the monitoring and analysis module. In the detection module the driver wears a SIMMERv.3 sensors on his/her right foot which transfer signals through Wi-Fi to a Raspberry Pi 3 with equipped with a SIM card. Raspberry Pi device receives the gyroscope and acceleration signals from the SHIMMER sensors. And the research purposes a Deep Learning (DL) model that uses deep convolutional neural network (DCNN) architecture in a cloud computing environment. According to the research the model consists of two blocks for feature representation and classification to make the model applicable in limited IoT devices such as Raspberry Pi.

A survey paper [2] by Fangming Qu, Nolan Dang, Borko Furht and Mehrdad Nojoumian has conducted a deep exploration in safety concerns related to autonomous vehicles and highlights the critical necessity of an AI-based system for driver behavior classification. Furthermore, the survey paper provides a detailed explanation on development of unified AI system that exceeded the current classification techniques in depth and breadth. The paper studies driver behavior classification and evaluation in autonomous vehicles deeply and provides a detaied record of those techniques. [Figure 1]

A research [3] by Hang-Bong Kang discusses various methods available to determine the drowsiness and distraction state of a driver. Driver drowsiness is detected using driver behavior such as visual features, non-visual features and driving performance. PERCLOS, eye-closure duration (ECD), frequency of eye closure (FEC) are visual feature-based systems used to detect driver drowsiness. According the research the driver distraction is detected by analyzing drivers' head pose and gaze direction. Furthermore, The paper discusses the importance of predicting unsafe driving behavior and explains prediction methods based on facial expression and car dynamics

The research [4] by conducted by V. Sanjay Kumar, S. Nair Ashish, I. V. Gowtham, Ashwin Balaji, E. Prabhu discusses about design and development of a driver assistance system using signal processing and embedded tools. The research mainly focused on development of a prototype system that would not only monitor the driver's physiological state but also alert both the driver and the passengers of the prevailing situation using Internet of things. The prototype system includes three input extraction modules, the driver drowsiness detection mechanism, Alcohol content detection module and Vehicle crash detection mechanism. A Raspberry Pi minicomputer and interrelated software and hardware has been used for this prototype. The Raspberry Pi board performs the algorithmic processes based on the user- defined functions and extracts the output. The end-system is based on the IoT belonging to the alert phase where the SIM800c microcontroller plays an important role as it establishes the connectivity with the networks.

The research [5] by Sameer Rafee, Xu Yun, Zhang Jian Xin and Zaid Yemeni proposed a system for eye movement analysis and prediction. The proposed system includes functions for three-type eye movement classification and prediction data consistency with a various and wide range of components. The proposed system is heavily relied on Module Architecture.

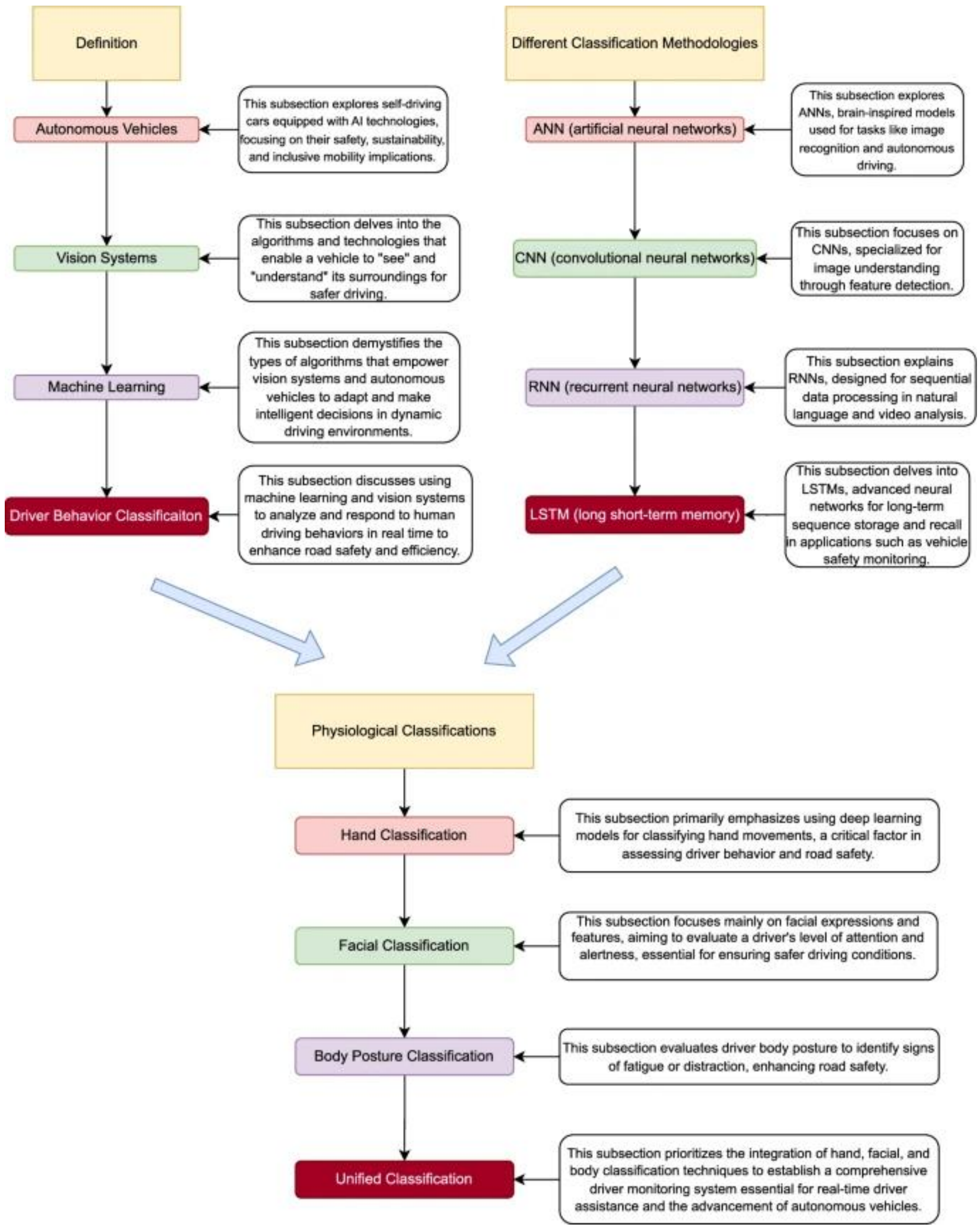

Figure 1: Roadmap of driver behavior monitoring systems

Research Gap

According to the literature review, there are several studies on driver behavior monitoring. The researches use a verity of methods and sensors to analyze driver behavior. But there is a lack of such technologies that can satisfy the needs of deaf drivers. According to the literature review following gaps have identified making the existing systems ill-equipped to handle specific needs of deaf people.

References	Use facial movements to identify the state of the driver.	Analyse driving performance.	Use facial movements and driving performance to analyse driver responses to alert system.	Data analysis and reporting.
Research A	✗	✓	✗	✗
Research B	✓	✗	✗	✗
Research C	✓	✓	✗	✗
Research D	✓	✗	✗	✗
Proposed System	✓	✓	✓	✓

Figure 2: Comparison Between Existing Systems

According to the literature review modern driver behavior monitoring systems uses mainly eye and facial movement analysis and driving performance analysis in the system as a data resource. Most of the existing systems utilizes ether one of the above methods while the literature review reveals few researches that utilizes both mainly eye and facial movement analysis and driving performance analysis in their systems. But since neither of those systems facilitates the needs of deaf drivers a significant gap has been revealed.

In the literature review it was noted that most of the researches are focused on either on of the methods, eye and facial movement analysis or driving performance analysis not in both. There for in the proposed system bridges the gap seen by integrating both facial movements and driving performance, indicating a more comprehensive approach giving the system to monitor that the driver is correctly and timely responding to the hazard detection system.

The proposed system addresses a significant gap by including data analysis and reporting, which is missing in all the other research references. This feature could enhance the system's effectiveness in real-world applications by providing actionable insights based on data.

Research Problem

Deaf drivers face unique challenges on the road due to their inability to perceive auditory cues. These cues are extremely important for timely responses to emergency situations. Traditional vehicle safety systems, while effective for the general population, often fail to cater to the specific needs of deaf drivers, who rely more heavily on visual and tactile information. As a result, deaf drivers may not receive the critical alerts they need in a timely manner, increasing the risk of accidents and reducing their overall driving safety. With advancement of vehicle accessibility, more deaf individuals are now starting to use vehicle daily. With the growing number of deaf drivers on the road a lack of technologies to facilitate their special needs have immerged due to most of the vehicles were not being designed for their specific needs. All of the current vehicle technologies and safety systems are developed for the general population which over looks the special needs of a deaf driver.

The aim of this research is to design and develop a comprehensive driver behavior monitoring and reporting system specifically designed to facilitate the needs of a deaf driver. To facilitate a deaf driver this proposed system should be capable of monitoring driving behavior, alerting driver and reporting and feedback. Driver behavior and driving responses such as lane changed average speed is needed to be monitored. And providing real time non-auditory alerts in critical events or hazards, using visual, haptic, or other sensory feedback mechanisms is also discussed thin this research. Finally, successful methods of generating reports and visualizations on driving performance that can be used for self-assessment is further discussed.

This expansion emphasizes the relevance and importance of the research problem, making it clear that addressing these gaps will not only improve the lives of deaf drivers but also push the boundaries of automotive technology and inclusivity.

Objective

Main Objective

Autonomous IoT Enabled Hazard detection and Communication System for Deaf Drivers is a driving assistant build focused on facilitating unique needs of deaf drivers. It combined new and previously used technologies to provide a seamless experience.

The main objective of this component is the design and development of a comprehensive driver behavior monitoring system for deaf drivers. This system utilizes a camera setup and a series of sensors alongside with DL models trained to analyze the driver's eye and facial movements and driving performance. Computer Vision is used for real time video analysis to monitor traffic signals, lane discipline, and other visual cues. In the proposed system DL models are used to analyze sensor data, detect patterns, and identify unsafe driving behaviors.

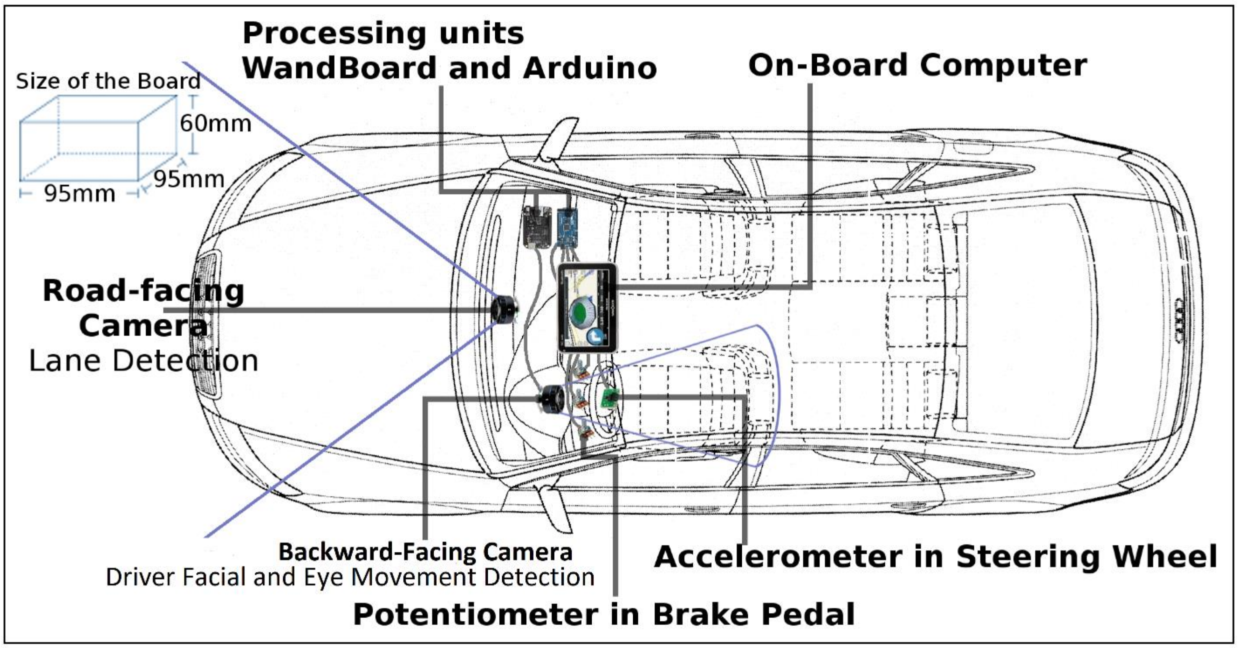

Figure 3: Proposed Sensor Setup

In the proposed system a verity of IoT devices are being used. Two cameras, one facing the road to monitor lane keeping and driving performance the other facing the driver to observe the driver behavior. All the processers are being handled by the processing unit [Figure 3] that uses a Arduino or raspberry Pi board.

By leveraging these AI methods and IoT devices, the system can effectively monitor and improve the driving behavior of deaf drivers, ensuring their safety and enhancing their overall driving experience.

Sub Objectives

Driver Eye and Facial Movement Analysis

Driver eye and facial movement analysis is focused on understanding and interpreting subtle movements of the drivers’ eye and face to determine their attentiveness, forces and overall fitness to drive. Eye and facial movement analysis have broad applications in enhancing road safety by the development of autonomous vehicles.

Eye and facial movement analysis are integral to Driver Behavior Monitoring, which are designed to assess whether a driver is paying attention to the road, is fatigued, or is distracted. The main two applications of the eye and facial movement analysis in Driver Behavior Monitoring are alertness detection and fatigued detection. By tracking eye movements such as gaze direction, blink rates and eye closure these systems can determine if a driver is becoming drowsy or inattentive, triggering alerts or taking corrective actions. Gaze detection tracks where the driver is looking helping to determine if they are focused on the road or the hazard alerting system or whether they are distracted. Blink rates analyses the frequency and duration of the blinks, which can be used to determine the drivers’ drowsiness and fitness to drive. And the head pose estimation determines the orientation of the driver’s head to ensure the driver is focused at the road rather than being distracted.

High-resolution infrared cameras are commonly used to capture eye and facial movements. These are often paired with depth sensors to provide 3D facial mapping. Advanced AI and ML algorithms are employed to analyze the captured data, identifying patterns that correlate with specific driver states such as fatigue or distraction. Deep Learning (DL) models such as especially convolutional neural networks (CNNs) are used in these systems to handle and process large amounts of complex visual data. These models analyses each frame from the video recorded by the car cameras and extracts relevant features related to eye movements, facial expressions, and head position.

DL models needs to be trained to estimate where the driver is looking at by analyzing the position and orientation of the eyes in real-time. This is crucial for determining whether the driver is focused or distracted. Recurrent neural networks (RNNs) or long short-term memory (LSTM) networks are often used to analyze sequences of images to detect blinks and perfect for blink detection. Parameters such as prolonged blinking and increased blinking rates are strong indicators of fatigue and drowsiness, which the system can use to alert the driver. Also, the DL models needs to be trained in three-dimensional (3D) head pose detection. DL models can analyze the orientation of the driver’s head in 3D space, determining if the driver is looking at the road, at a distraction, or potentially at an area of danger. When combined with the gaze detection the DL models can produce a comprehensive assessment in drivers’ attentiveness.

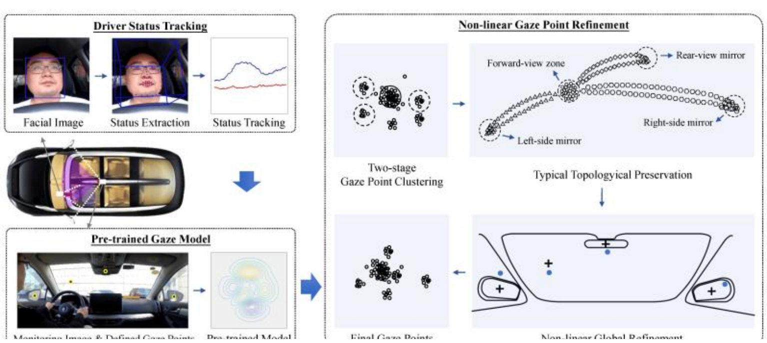

Figure 4: Eye and Facial Movement analysis using Deep Learning

Driving Performance Analysis

Areas of lane keeping, acceleration and braking pattern analysis is a crucial aspect of understanding driver behavior. Driving performance analysis (DPA) is used in the proposed system to monitor the drivers' attentiveness towards the hazard detection system. The DPA system determines the driver is correctly and timely responding to the proposed hazard detection system by analyzing the drivers' performance. This research focuses on how driving performance in these areas is analyzed, with a focus on the role of advanced technologies, including deep learning and other data-driven approaches.

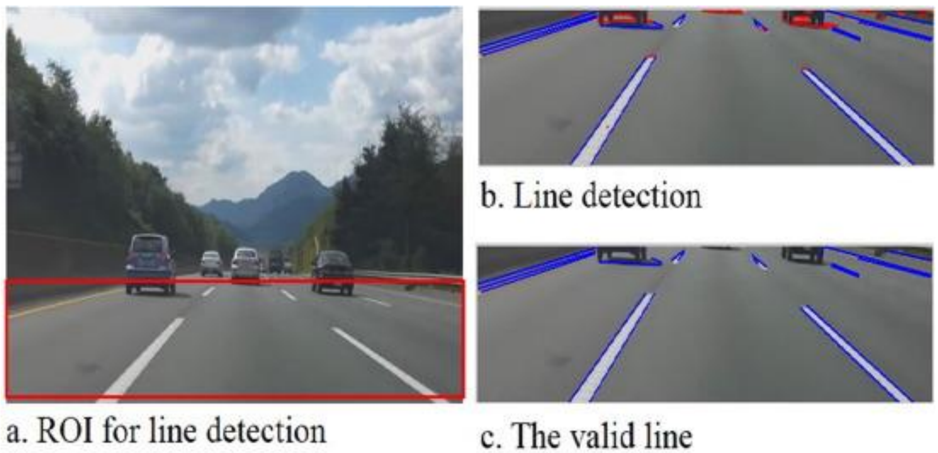

Figure 5: Lane Detection

Lane keeping performance is measured by two metrices. Lane deviation measures the extent to which a vehicle drifts from the center of the lane. Frequent or large deviations can indicate driver distraction or drowsiness. Lane change behavior analyses the way the driver changes lanes, including the use of indicators and the smoothness of the maneuver. By implementing Computer Vision techniques such as image processing to detect lane markings and monitor the vehicle's position relative to them and convolutional neural networks (CNNs) are to be used in the proposed system.

Braking performance is crucial for preventing rear-end collisions and ensuring safe stopping distances. In the proposed system braking performance refers to how effectively a driver uses the vehicle's brakes to slow down or stop. To analyze braking performance two matrices are used. Braking Reaction Time measures the time between the moment a driver perceives the need to brake and when the driver apply the brakes. Shorter reaction time indicates higher level of attentiveness. And secondly Deceleration Rate Analyzes how quickly the vehicle slows down, which can indicate whether the driver is braking too harshly or too gently.

Acceleration performance involves how a driver controls the vehicle's speed, including how they accelerate from a stop or while driving. Smooth and appropriate acceleration is key to maintaining vehicle stability and passenger comfort. This measurement is analyzed using two matrices. Acceleration Rate Evaluates how quickly the vehicle reaches a certain speed from a stop or during driving. Speed Management Analyzes how well a driver maintains appropriate speeds in various driving conditions, including adherence to speed limits.

Reporting and Data Visualization

Reporting and data visualization play a crucial role in effectively communicating the insights derived from driving performance analysis. The research also discusses how reporting and data visualization can be effectively utilized in the context of driver eye and facial movement Analysis and driving performance analysis, focusing on lane-keeping, braking, and acceleration.

Reporting and visualizations enhances the driver's awareness towards their driving weaknesses and allowing self-improvement. The primary objective of reporting and data visualization present data in a way that clearly communicates key insights and findings from driving performance analysis. And also, to Support Decision-Making by providing a clear view of driving behaviors and performance metrics, these tools support decision-making processes, such as training, policy formulation, or vehicle design.

The proposed system is meant to generate several reports allowing the driver to help in tracking and monitoring driver performance over time, allowing for the identification of trends, patterns, and areas of improvement. By measuring matrices like average lane deviation and braking reaction time Summery Reports provides a brief overview of driving performance, typically over a specific period of time. To offer in-depth analysis Detailed Reports are created using matrices such as lane departures, gaze direction and blink rate. These reports include data from the hazard detection system and if a hazard is notified when and if the correct response was taken by the driver.

In the proposed system interactive dashboards are introduced to provide a comprehensive view of driving performance using interactive elements like sliders, filters, and drill-down capabilities. Users can customize their view to focus on specific metrics or time periods.

Methodology

Overall System Diagram

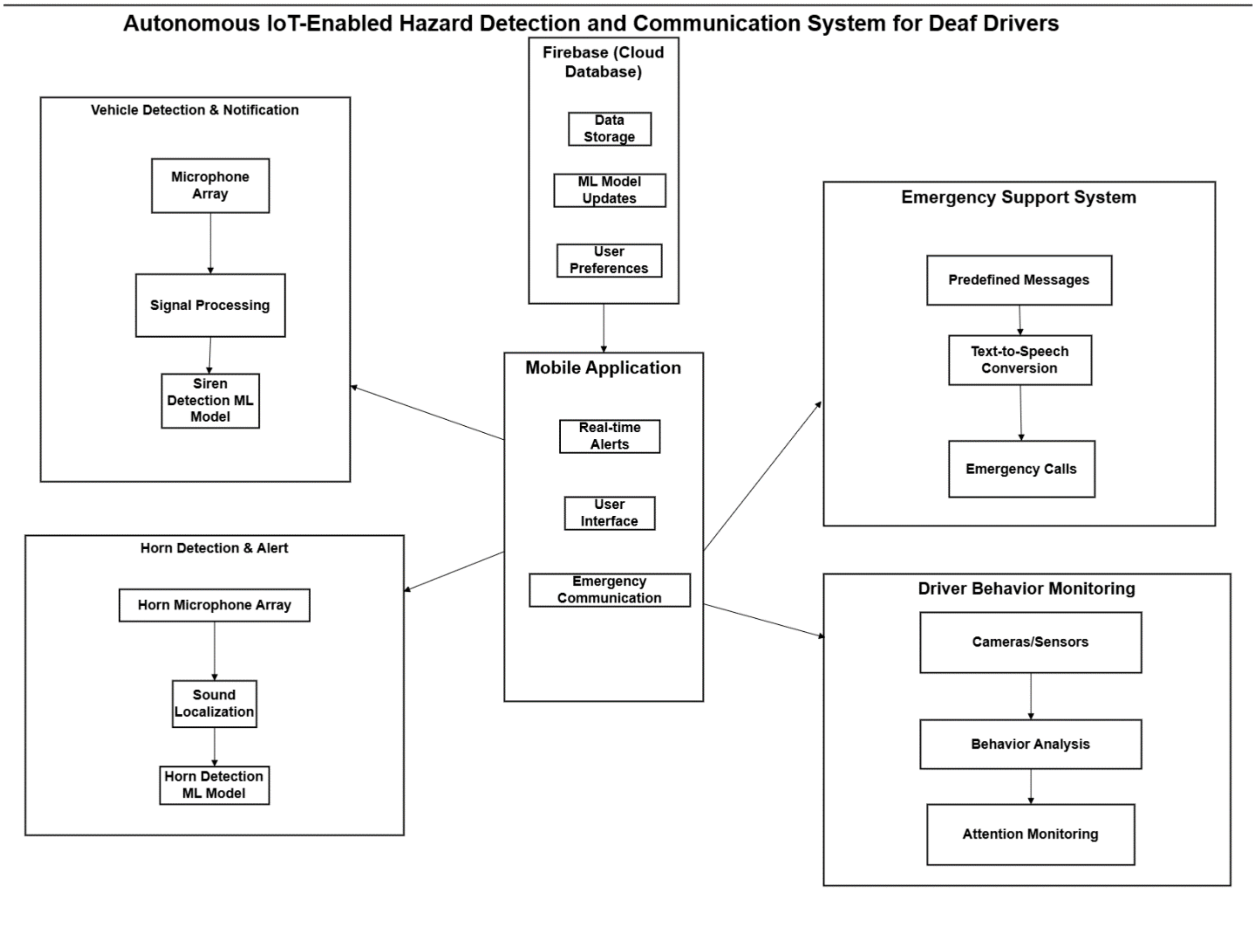

Figure 6: Overall System Diagram

Individual System Diagram

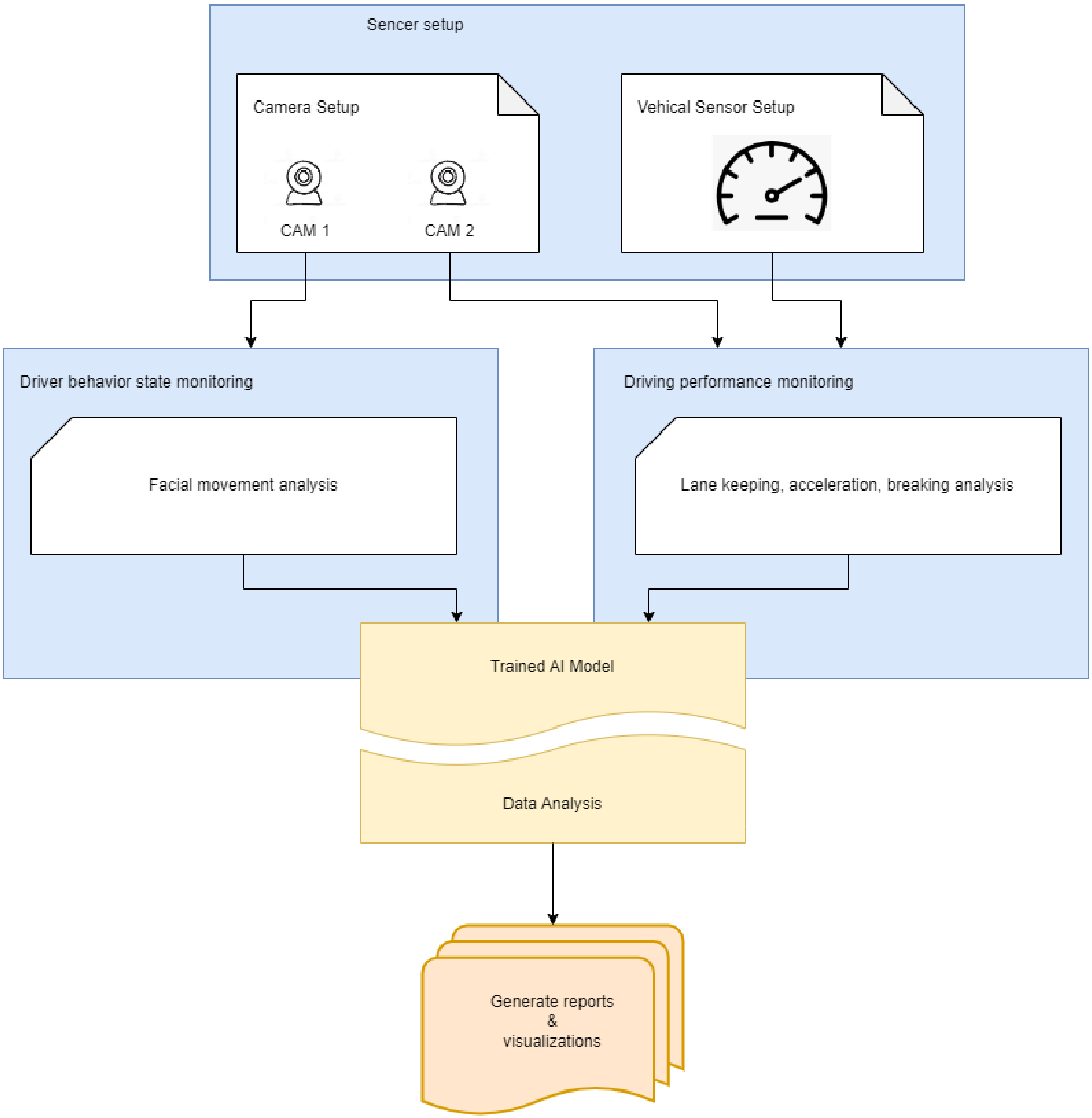

Figure 7: Individual System Diagram

Commercialization of the Project

Commercializing an Autonomous IoT Enabled Hazard detection and Communication System for Deaf Drivers involves several steps.

- **Target Market Identification:** Focus on markets with significant numbers of deaf drivers. Research the size of this demographic in various regions and identify specific needs that aren't being met by existing systems.
- **Competitor Analysis:** Analyze current products and solutions that serve similar purposes, including mainstream driver monitoring systems and niche products for drivers with disabilities. Identify gaps that your system uniquely addresses.
- **Pricing Strategy:** Develop a pricing strategy that reflects the value of the system while remaining affordable for the target market. Consider offering different pricing tiers based on features or subscription models for ongoing data analysis and reporting.
- **Privacy and Data Security:** Given that the system will collect and analyze personal data, ensure that robust data protection measures are in place.
- **Community Engagement:** Engage with the deaf community through workshops, demonstrations, and collaborations. This can also provide valuable feedback and foster a sense of ownership among users.

Commercializing an Autonomous IoT Enabled Hazard detection and Communication System for Deaf Drivers requires a strategic approach focusing on the specific needs of the target audience. By building strong partnerships while protecting intellectual property the project can be successfully transited from a research initiative to a market-ready product.

Algorithms Used in the Models

To ensure a robust and accurate driver behavior monitoring system tailored for deaf drivers, we adopted a **multimodal deep learning approach**, combining both visual data (camera feed) and temporal sensor data (e.g., accelerometer, gyroscope, steering angle). This chapter details the deep learning algorithms used in the development of the system, along with their individual contributions and how they were integrated.

1. Convolutional Neural Networks (CNN) for Visual Input Analysis

A **Convolutional Neural Network (CNN)** was used to process the visual input captured from the in-vehicle camera. The model architecture is based on **MobileNetV2**, a lightweight and efficient convolutional neural network pretrained on ImageNet, and fine-tuned for our custom dataset containing various driver behavior classes (e.g., texting, drinking, operating the radio).

Model Architecture

- **Base Model**: MobileNetV2 with reduced width multiplier (alpha=0.05) to ensure efficiency on edge devices.
- **Feature Extraction**: The pretrained convolutional layers extract spatial features such as hand movement, head orientation, and face gestures.
- **Custom Layers**:
  - Reshape + Dense layers to adapt the extracted features.
  - Dropout and Flatten for regularization and dimensionality reduction.
  - Final Dense layer with softmax activation for classification across predefined visual behavior classes.

Optimization and Training

- Loss Function: Categorical Crossentropy
- Optimizer: Adam
- Fine-tuning: The last 65% of layers were unfrozen and fine-tuned after initial training.
- Metrics: Accuracy

2. Recurrent Neural Networks (RNN) with LSTM for Sensor Data Analysis

For processing temporal sensor data such as acceleration, braking, and steering angle variations, we employed **Long Short-Term Memory (LSTM)** networks — a variant of Recurrent Neural Networks (RNN) designed to model sequential dependencies over time.

Model Architecture

- **Input**: Time-segmented sequences from sensor readings (e.g., 14-second windows of accelerometer, gyroscope).
- **LSTM Layers**:
  - LSTM(64, return_sequences=True) for capturing low-level temporal features.
  - LSTM(32) for abstracted pattern recognition.
- **Fully Connected Layers**:
  - Dense layer with ReLU activation.
  - Final Dense layer with softmax activation for behavior classification.

Preprocessing

- **Label Encoding** for categorical columns
- **Min-Max Normalization** for all features
- **One-Hot Encoding** for target behavior labels
- **Reshaping** input data into (samples, timesteps, features) format for LSTM compatibility.

Training Configuration

- Loss Function: Categorical Crossentropy
- Optimizer: Adam
- Validation Split: 20%
- Epochs: 50
- Batch Size: 32
- Callbacks: Model Checkpoint to store the best performing model

3. Multimodal Feature Fusion Layer (Planned Integration)

To enhance the performance of the system through multi-source information, we proposed a **fusion layer** that integrates both CNN-derived and LSTM-derived feature embeddings.

Fusion Strategy

- **Feature-Level Fusion**: Concatenation of dense feature vectors from the visual and sensor pipelines.
- **Classifier Head**:
  - Fully connected Dense layers to learn inter-modal correlations.
  - Softmax layer for final driver behavior prediction.
- **Alternative Approach**: Incorporation of attention mechanisms or transformer blocks for dynamic weighting of modality importance.

Algorithm	Modality	Purpose
CNN	Camera	Classify visual driver behaviors
LSTM	Sensor	Classify temporal driver behaviors
Fusion Layer	Combined	Improve classification through multimodal integration

This multimodal learning pipeline ensures that both **spatial visual cues** and **temporal sensor patterns** are effectively leveraged, providing a more accurate and inclusive driver behavior monitoring solution for the deaf community.

Evaluation Metrics Used in the Models

To assess the performance and reliability of our driver behavior classification models, we used a combination of **standard classification evaluation metrics**. These metrics provided insight into both the **accuracy** of the models and how well they generalized to unseen data.

1. Evaluation Metrics for CNN-Based Visual Input Model

The CNN model for classifying driver behaviors from visual input was evaluated using a comprehensive set of performance metrics. These metrics were derived from both statistical scores and a confusion matrix, offering insight into the model's classification accuracy across ten behavioral classes. The model utilized a transfer learning approach based on MobileNetV2, achieving strong performance on the test dataset.

1. Area Under ROC Curve (AUC)

The model achieved an **Area under the ROC Curve (AUC) of 1.00**, indicating perfect separation between the classes. This reflects a high capability of the model to distinguish between correct and incorrect classifications.

2. Weighted Average Metrics

- **Precision:** 0.96
- **Recall:** 0.96
- **F1 Score:** 0.96

These weighted average values demonstrate that the model consistently performs well across all classes, balancing both the correctness of predictions (precision) and the ability to identify all relevant instances (recall). The high F1-score reflects strong overall performance in the multi-class classification setting.

3. Class-Wise Accuracy from Confusion Matrix

The confusion matrix reveals detailed per-class performance. The diagonal values indicate the percentage of correct predictions for each class. The model performed particularly well across most driver behavior classes:

	DRINK	HAIR-/	NORM	OPER/	PHON	PHON	REACH	TALKII	TALKII	TALKII	UNCEI
DRINKIN(	93.4%	0.2%	0%	0.2%	0%	0.2%	0%	1.0%	0.4%	0.4%	4.1%
HAIR-ANI	0.8%	88.4%	0.3%	0.3%	0.3%	0.3%	0.5%	0%	0.5%	0.5%	8.2%
NORMAL-	0%	0.4%	92.0%	0.2%	1.7%	0.4%	0.2%	0.2%	0%	0.4%	4.6%
OPERATII	0%	0.2%	0%	96.2%	0.2%	0%	0%	0.6%	0%	0.2%	2.5%
PHONE-II	0%	0.2%	0.6%	0.4%	95.5%	0%	0%	0%	0%	0%	3.4%
PHONE-II	0.2%	0%	0.2%	0%	0%	96.4%	0%	0%	0.2%	0%	2.9%
REACHIN(	0%	0%	0.3%	0%	0%	0%	97.5%	0%	0.3%	0.8%	1.3%
TALKING-	0%	0.4%	0.6%	0.2%	1.0%	0%	0.2%	91.3%	0.2%	0.6%	5.4%
TALKING-	0.6%	0.2%	0%	0%	0%	0.2%	0.2%	0%	95.2%	0.2%	3.2%
TALKING-	0%	1.2%	1.5%	0.7%	0.5%	0.2%	0.5%	0.2%	0%	91.0%	4.1%
F1 SCORE	0.96	0.92	0.94	0.97	0.96	0.98	0.98	0.94	0.97	0.94	

Figure 8: Model performance over classes

The evaluation confirms that the CNN model is highly effective in recognizing and classifying complex driver behaviors from visual data. With a near-perfect AUC and high per-class accuracies, the model is well-suited for real-time driver monitoring applications. Small misclassifications between visually similar behaviors may be further reduced through additional fine-tuning or multi-modal integration with temporal sensor data.

2. Evaluation Metrics for LSTM-Based Temporal Sensor Model

The LSTM model was trained on time-series sensor data (accelerometer, gyroscope, and steering angle). Similar to the CNN model,

- **Loss (Categorical Crossentropy)**

This was monitored to determine how well the model fit the training data and how well it generalized to validation data.

- **Precision, Recall, and F1 Score (Post-Evaluation)**

For deeper analysis, we used the classification report to evaluate:

  - **Precision**: Correctly predicted positive observations out of total predicted positives.
  - **Recall**: Correctly predicted positive observations out of total actual positives.
  - **F1 Score**: Harmonic mean of Precision and Recall.

```
from sklearn.metrics import classification_report

print(classification_report(y_true, y_pred, target_names=class_labels))
```

By applying a comprehensive set of evaluation metrics, we ensured that both models were thoroughly assessed for accuracy, robustness, and class-wise performance. These metrics not only guided the training process and model selection but also played a critical role in identifying potential improvements. The consistent use of these evaluation strategies across both the CNN and LSTM models allowed for a clear understanding of each model's strengths and limitations in recognizing diverse driver behaviors.

Testing and Implementation

Implementation Overview

The proposed system was designed to recognize and classify driver behaviors using a hybrid approach involving both **visual data** (images or video frames) and **temporal sensor data** (accelerometer, gyroscope, and CAN bus signals). The system was implemented using two deep learning pipelines:

- A **CNN-based model** using transfer learning (MobileNetV2) to process visual inputs.
- An **LSTM-based RNN model** to process temporal sequences of sensor data.

Both models were developed using **TensorFlow and Keras**, leveraging the Python programming language. Data preprocessing and model evaluation were conducted using tools such as **NumPy, pandas, scikit-learn**, and **Matplotlib**.

Testing Methodology

Both models were tested using pre-labeled datasets for objective performance evaluation. The data was split into **training (80%)** and **testing (20%)** sets to ensure unbiased model validation.

- **CNN Model Testing**

The CNN model was tested on a dataset consisting of ten classes representing different driver behaviors:

- Normal driving
- Texting (left and right)
- Talking on the phone (left and right)
- Operating the radio
- Drinking
- Reaching behind
- Hair and makeup
- Talking to a passenger

Testing involved feeding the trained model with unseen images from the test set and comparing the predicted class with the true label. The results were evaluated using classification metrics such as **accuracy, precision, recall, F1 score,** and **confusion matrix**.

- **LSTM Model Testing**

The LSTM model was trained and tested on temporal sensor sequences segmented using a fixed-size sliding window. Each sequence represented a specific behavior label and was passed through the LSTM network to predict the associated class. Testing accuracy and loss were tracked over multiple epochs, and the best-performing model (based on validation accuracy) was saved and used for final evaluation.

Real-Time Feasibility and Integration

To assess deployment feasibility, both models were tested under simulated real-time conditions. Sensor data was streamed from recorded files, while images were fed from a webcam/video feed. The combined inference time for both models was evaluated to ensure they meet real-time constraints. The system was capable of producing behavior classifications with minimal latency, making it suitable for integration into driver assistance systems.

Furthermore, implementation included:

- **Data storage** using Firebase Realtime Database for live updates.
- **Mobile frontend (React Native)** for real-time monitoring and behavior alerts.

Challenges During Implementation

Several challenges were encountered and resolved during the testing and implementation phases:

- **Data imbalance:** Some behaviors were underrepresented, requiring data augmentation and oversampling techniques.
- **Sensor noise:** Raw sensor values contained irregularities that needed smoothing and normalization.
- **Confusion between similar classes:** Actions like talking vs. texting exhibited high visual similarity, which was partially resolved using additional temporal context.

The testing and implementation phase demonstrated that the developed system performs reliably in identifying driver behaviors using both visual and sensor data. The models were successfully trained, validated, and tested in controlled environments, and the system architecture supports potential deployment in real-world vehicle monitoring applications.

Research Findings

CNN Model Findings (Visual Behavior Detection)

The CNN model was trained using **transfer learning** based on MobileNetV2 architecture to classify driver behaviors from visual inputs (e.g., camera frames). The evaluation yielded the following results:

- **High overall performance:** The model achieved an **Area Under the ROC Curve (AUC)** of **1.00**, and **weighted average precision, recall, and F1-score of 0.96**, demonstrating robust classification capability across 10 behavior classes.
- **Effective class separation:** The confusion matrix revealed high per-class accuracies, with behaviors like **normal driving**, **drinking**, **talking on the phone**, and **operating the radio** classified with over **90% accuracy**.

- **Challenges in visually similar actions:** The model showed slightly reduced accuracy (e.g., around **88%** for *hair and makeup*) when distinguishing between visually similar or occluded actions, indicating a potential benefit from incorporating temporal context.

These findings support the suitability of transfer learning for in-vehicle vision-based systems, especially where computing resources may be limited.

LSTM Model Findings (Temporal Sensor Behavior Detection)

The LSTM-based RNN model focused on recognizing driving behaviors based on **accelerometer**, **gyroscope**, and **CAN bus sensor data** over time. The key findings include:

- **Temporal modeling improves classification:** The LSTM model effectively captured sequential dependencies in sensor data, achieving high validation accuracy (over **95%**) in classifying dynamic behaviors such as **turning**, **braking**, and **acceleration**.
- **Preprocessing is critical:** Proper data normalization and sequence segmentation (e.g., 14-second windows) significantly impacted performance, confirming that preprocessing is crucial for time-series models.
- **Generalizability across drivers and vehicles:** The model performed consistently across data from different vehicle types and driver profiles, suggesting good adaptability.

These results confirm that LSTM networks are highly effective for modeling temporal driving patterns, making them a valuable complement to vision-based classifiers.

Real-Time Applicability

- The models demonstrated **low latency inference** (under 200ms per prediction), supporting their use in real-time systems.
- The ability to **stream and classify live sensor and video data** validated the feasibility of deploying this system in smart vehicles or mobile applications.
- Integration with Firebase and a React Native app enabled real-time visualization and alerts, making the system accessible and user-friendly.

Contribution to Driver Safety and Deaf Accessibility

One of the unique contributions of this research is its focus on **assisting deaf drivers** through non-auditory monitoring and feedback. The system's ability to:

- Detect driver distraction or risky behavior,
- Provide real-time alerts via mobile interfaces,
- Operate without reliance on sound-based cues,

...makes it a valuable assistive technology that aligns with inclusive transportation goals.

The research successfully demonstrated that a multimodal deep learning approach—combining CNN for visual analysis and LSTM for temporal sensor data—can effectively recognize a wide range of driver behaviors. The system's high accuracy, real-time capability, and extensibility offer promising opportunities for deployment in intelligent transportation systems, with particular benefits for deaf drivers and safety-critical environments.

Software Specification

Functional Requirements

1. The system should collect data from various sources, including accelerometers, cameras, and other sensors.
2. The system must continuously monitor driving behavior using sensors and cameras.
3. The system should analyze driving behavior using AI algorithms to detect patterns and anomalies.
4. The system should generate detailed reports on driving behavior, highlighting areas of improvement and compliance with safety standards.
5. The system should allow users to customize settings and feedback preferences based on their needs.

Non – Functional Requirements

1. Performance: The system should handle large volumes of data efficiently without performance degradation.
2. Reliability: The system should operate consistently and accurately under different driving conditions.
3. Accessibility: The system should follow accessibility guidelines to ensure it meets the needs of deaf drivers.
4. Battery Life: For portable and battery-powered components, the system should have an adequate battery life to ensure continuous operation.

Tools and Technologies

1. Android Application development
2. Deep Learning (CNNs/ RNNs/ LSTM)
3. Raspberry Pi
4. Cameras and other sensors

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