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IoT-based Automatic driver distraction detection

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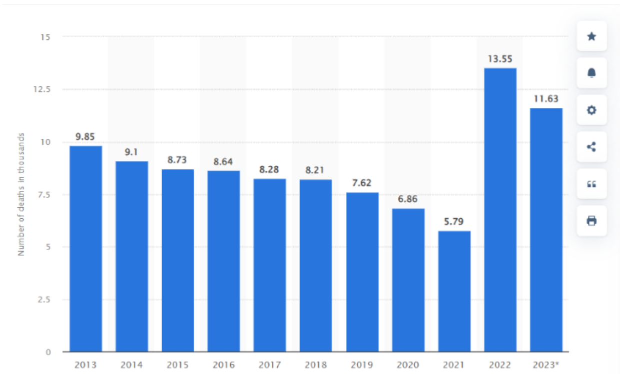
Content

1 Introduction

1.1 Background and Context

Every day, thousands of people die from road accidents around the world. Many car accidents occur around the world and almost all are caused by human or driver errors. According to WHO (World Health Organization 2023), the number of deaths caused by road accidents is nearly 1.19 million each year and on average. Road accidents are a major problem in many developing countries, including Vietnam. In 2023, the number of deaths caused by traffic accidents amounted to approximately 11,628 cases in Vietnam. To address this, Todt advocated for comprehensive solutions, including public education, stricter law enforcement, and improvements in vehicle safety standards, protective gear, and road infrastructure.

According to the statistics of Vietnam (Statista 2023), in 2022, the number of deaths caused by road accidents saw a quite huge figure, more than 11,000 cases. This indicated a decrease from the previous year. From 2013 to 2021, the number of traffic deaths has gradually declined, then increased dramatically in 2022, with the number of deaths due to crashes double than in 2021, over 13,000 cases in 2022 compared to nearly 5,800 cases in 2021. In particular, most road accidents occur due to the abnormal behavior of the driver such as the driver eating or drinking, operating the radio, talking to others, texting or talking on the smartphone, etc. To reduce such nonprofessional activities, IoT-based deep learning models can play a significant role by detecting distracted driver activities and notifying the driver to stop while these activities occur to prevent accidents.



1.2 Research Questions

1. How can deep learning models be effectively integrated with IoT architectures for real-time distracted driver detection?

2. What types of distractions can be accurately detected using a lightweight deep learning mode suitable for edge devices?

3. What are the trade-offs between detection accuracy and real-time performance when deploying these models on IoT devices?

4. How does the inclusion of multimodal IoT data (e.g. camera, GPS, accelerometer) improve the performance of distraction detection systems?

1.3 Relevance and Importance of the Research

This research aims to develop an IoT-based deep learning framework for real-time detection of distracted driving behaviours. The goal is to create a practical and efficient solution suitable for low-power edge devices like Raspberry Pi. This study addresses the gap between theoretical model development and real-world deployment, offering insights valuable to the automotive industry, transportation safety, and smart city initiatives. The findings could contribute to safer driving environments and support future in-vehicle safety policies.

2 Literature Review

2.1 Summary

Our system diagram is based on Bidhan[1] [2024] with some modification to the hardware used. As for our model, we will be using a CNN-based model, which is better suited in image-related tasks such as sleepiness detection.

2.2 Key Concept

Machine learning with deep learning in particular allows our detection system to learn from observation of drivers and prior data training. Using camera sensors, we hope to develop a model that can accurately determine the behaviour of our subject such as sleepiness and drowsiness. Based on the findings and results of Md.M. Islam[2] [2022], we will be using a CNN model.

3 Research design and methods

3.1 Research design

This study uses a quantitative, experimental design to develop and evaluate deep learning models for distracted driver detection within an IoT framework. The State Farm dataset will support model training, while real-time tests on IoT devices will assess performance. The focus is on balancing accuracy and efficiency for practical deployment.

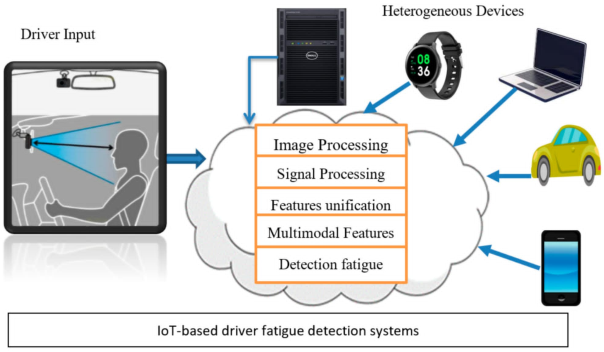
3.2 Methods and Sources

3.2.1 Tools & Technologies:

- **Deep learning Frameworks:** PyTorch for model development.
- **IoT Hardware:** Raspberry Pi.
- **Sensors and Inputs:** a mounted camera (webcam or Raspberry Pi Camera Module (for real-time image input.
- **Dataset:** State Farm Distracted Driver dataset on Kaggle; optionally, a small custom dataset may be collected for edge testing.

3.2.2 Procedures:

1. **Model Development:** Design and train CNN-based models (e.g, MobileNetV2, ResNet18, EfficientNet-lite) optimized for embedded deployment.
2. **Model Optimization:** Use quantization and pruning techniques to make the model lightweight for IoT deployment.
3. **Integration with IoT:** Implement the trained model on a Raspberry Pi for real-time image classification.
4. **Data Collection for Evaluation:** Capture test video/image data from simulated driving environments to validate the system's detection performance.
5. **Evaluation Metrics:** Accuracy, precision, recall, F1-score (for model performance), and latency, memory usage, and power consumption (for IoT performance).



3.2.3 Practical Considerations

- **Hardware Constraints:** IoT devices have limited memory and processing power, which can restrict the complexity of deployable models. To address this, model compression techniques will be applied, and lightweight architectures will be prioritized.
- **Data Generalization:** Models trained on a public dataset may not generalize well to new driving environments. To reduce this issue, testing will include custom real-world samples.
- **Ethical Concerns:** Once collecting enough original video data, participants will be informed, and their consent will be obtained. All captured data will be anonymized and stored securely.
- **Environmental Variables:** Lighting, motion blur, and occlusion in real driving conditions may impact performance. The system will be tested in various lighting conditions to evaluate robustness.

4 Implications and contributions to knowledge

The Internet of Things (IoT) has become a game-changer in our everyday life, revolutionising how we interact with technology and the world as a whole. As traffic accidents become an urgent public issue, detecting distracted driving behaviours with IoT in real-time has the potential to reduce tragic incidents from occurring. The project is motivated by the need to improve road traffic safety around the globe using a machine learning model with the ability to categorize different forms of driver distraction through image data.

4.1 Practical Implications

Practically, our project can contribute to the improvement of road safety and the development of in-vehicle surveillance systems with the help of computer vision and machine learning techniques. By integrating sensor data from IoT devices like cameras - the system will continuously observe and detect if the driver is engaging in distracted driving activities. With such ability, the technology could be used by insurance companies like State Farm to evaluate drivers' behavior and reduce the risk of incidents or fatalities. The results can also inform transportation policies by providing evidence for new safety regulations, together with technology mandates related to vehicle operator monitoring systems.

4.2 Theoretical Implications

Theoretically, this work delves into the progressing fields of human-centered IoT, real-time data analytics, and cyber-physical systems. It explores and provides insights on how specific types of distraction correlate with drivers' behaviors. The project ponders questions in behaviour classification accuracy and contextual interpretation. In addition, the methodology may lay the groundwork for further studies on ethical usage of AI on the scalability of edge computing application in transportation systems, monitoring and data governance in vehicular networks.

5 References

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6 Research Schedule

Research phase	**Objectives**	**Timeline**
Literature review and dataset preparation	Review related work on IoT, distracted driver detection and select, preprocess the dataset for model training.	**Week 1-3**
Model training and optimization	Training a deep learning model for distraction detection and optimizing it for IoT deployment (e.g, model compression).	**Week 4-6**
IoT deployment and real-time testing	Deploying the model on IoT hardware, collecting real-time test data and evaluating system performance.	**Week 7-9**
Evaluation and analysis	Analysing results (based on accuracy, latency, resource use), finalizing findings and preparing conclusions.	**Week 10-12**