Université d’Ottawa

Faculté de génie



University of Ottawa

Faculty of Engineering

**ELG5901 Electrical Engineering Project**

**Project ID:** AI\_VALEO18\_2023

**Project Title:** Ice, snow, and water detection

**Sponsor:** Valeo

**Student Group ID:** 18

**Submitted By:**

|  |  |  |
| --- | --- | --- |
| Name | Student# | Email |
| Ahmed Ahmed Shafik | 300389391 | aalwa100@uotttawa.ca |
| Enas Ahmed Fouad | 300389379 | eali084@uOttawa.ca |
| Mohamed Hany Mohamed | 300389913 | mmost018@uottawa.ca |
| Mohamed Salah Mohamed | 300389919 | mgabr024@uottawa.ca |
| Mohamed Salem Hassan | 300389921 | mebai026@uottawa.ca |

# DEBI Support: Prof. Nermin Negied

# uOttawa Support: Dr. Murat Simsek

# VALEO Support: Eng. Reda Elhakim

# Graduate Program: Digital Egypt Builders Initiative (DEBI)

**Semester to Register:** 2023, Fall

**Table of Contents:**

1. Introduction

1.1 Problem Definition

1.1.1 Project Motivation and Importance

1.1.2 Problem Statement

1.1.3 Approach

1.1.4 Objectives and Learning Goals

1.2 Background  
1.3 Project Context

1.3.1 External Systems and Third-Party Interface

1.3.2 Collaborations and Dependencies

1.3.3 Availability and Accessibility

1. Design Overview

2.1 Requirements  
2.2 Detailed Design  
2.3 Implementation  
2.4 Testing

2.4.1 Data Plan

2.4.2 Validation & Verification

1. Overall Results and Analysis
2. Deployment Plan
3. Conclusions and Future Works
4. References

**Table of Figures:**

Figure 1: flowchart for solution design

Figure 2: Confusion Matrix for Best Implementation Model

Figure 3: final project implementation

Figure 4: Data Labels

Figure 5: ResNet50 Confusion Matrix

Figure 6: InceptionV3 Confusion Matrix

Figure 7: VGG16 Confusion Matrix

Figure 8: Streamlit testing

Figure 9: Application testing

**Table of Tables:**

Table 1: Comparative Analysis Based on F1-Scores

**Acronyms**

* AI - Artificial Intelligence
* YOLO - You Only Look Once
* VGG16 - Visual Geometry Group 16
* CNNs - Convolutional Neural Networks
* CNN - Convolutional Neural Network
* APIs - Application Programming Interfaces

**1. Introduction**

**1.1 Problem Definition**

**1.1.1 Project Motivation and Importance:**

This project, sponsored by Valeo, a leading global automotive supplier, focuses on enhancing road safety through advanced technology. Our team, consisting of master's students from the University of Ottawa specializing in Artificial Intelligence (AI) and Data Science, has been tasked with a critical and innovative challenge: detecting road hazards like snow, ice, and water to alert drivers and adapt vehicle operation accordingly. The importance of this project lies in its potential to significantly reduce road accidents, particularly in adverse weather conditions, thereby saving lives and minimizing property damage.

**1.1.2 Problem Statement:**

The primary problem we aim to address is the reliable and efficient detection of road hazards, specifically snow, ice, and water, using AI and machine learning techniques. Traditional methods of hazard detection often rely on physical sensors or manual observations, which can be unreliable or impractical in many situations. Our project seeks to develop a more robust solution that leverages advanced image processing and machine learning to detect these hazards accurately and in real-time.

**1.1.3 Approach:**

Initially, our strategy involved utilizing thermal images for hazard detection. However, due to the unavailability of these images, we pivoted to explore alternative data sources, including open-source data and video footage from dash cameras. Our revised approach encompasses the classification of road conditions into distinct categories (snow, ice, and clear), using frames extracted from video clips. We have applied various state-of-the-art models, such as You Only Look Once (YOLO), Resnet, Inception, and Visual Geometry Group 16 (VGG16), to identify the most effective architecture for our needs.

**1.1.4 Objectives and Learning Goals:**

Our objective is to develop a machine learning model capable of classifying road conditions with high accuracy, ensuring that the model can differentiate between clear roads and those presenting hazards like snow or ice. Throughout this project, we aim to deepen our understanding of machine learning applications in real-world scenarios, particularly in the field of autonomous driving and vehicle safety. Additionally, we hope to contribute valuable insights and tools that can be utilized by Valeo and the broader automotive industry to enhance road safety.

By the end of this project, we expect to have a well-tuned model with an intuitive user interface that allows for the classification of road conditions from video or image inputs, thereby offering a practical and innovative solution to a significant road safety challenge.

**1.2 Background**

The intersection of autonomous vehicle technology with weather hazard detection has attracted considerable attention due to its potential to significantly enhance road safety. This literature review delves into the integration of deep learning models into camera systems within autonomous vehicles, focusing on the application of these methodologies for weather hazard detection. The examination of pivotal research papers provides valuable insights into this dynamic and evolving domain. One distinct method [1] proposed involves the use of concrete-based sensors embedded in roadways and bridges to effectively identify hazardous conditions such as black ice, ice, and water. This proactive approach holds promise for preventing accidents and improving road safety. Another notable contribution [2] introduces a system that leverages Kinect technology to detect black ice. This system not only classifies different types of ice but also quantifies their distinct characteristics. Furthermore, the evaluation of Convolutional Neural Networks (CNNs) for road surface condition classification [3] underscores the superiority of deep learning methodologies over traditional techniques. An additional approach [4] presents a non-contact optical technology based on triwavelength backscattering measurements for black ice detection. This innovative method showcases the potential of harnessing advanced optical techniques for enhancing hazard detection. Moreover, a CNN-based approach [5] demonstrates exceptional accuracy in black ice detection, highlighting the prowess of deep learning in accident prevention. The utilization of pre-trained residual CNNs for real-time winter road surface condition monitoring [6] achieves remarkable classification accuracy. Exploring the fusion of infrared imagery [7], CNNs, and drone technology provides a means to predict black ice formation and deliver real-time alerts. This interdisciplinary approach demonstrates the multifaceted nature of research in this area. Furthermore, the use of drones equipped with thermal imaging cameras [8] contributes to more comprehensive black ice detection, enhancing overall road safety. Collectively, the findings from these research endeavors underscore the transformative potential of deep learning models in revolutionizing weather hazard detection within autonomous vehicles. This holds the promise of creating safer and more efficient transportation systems through proactive accident prevention.

**1.3 Project Context**

**1.3.1 External Systems and Third-Party Interfaces:**

Our project extensively interacts with various external systems and utilizes third-party interfaces, Application Programming Interfaces (APIs), tools, and systems, essential for gathering and processing the diverse data required for our image classification models.

1. **Roboflow:** This platform is crucial for organizing and preprocessing image data. It provides tools for annotating, transforming, and augmenting images, which is vital for preparing our dataset for machine learning models.
2. **Google Images:** As a vast repository of diverse images, Google Images will be instrumental in supplementing our dataset with a wide range of scenarios and conditions related to road hazards.
3. **YouTube and Film Clips:** To obtain real-world data, we plan to extract video footage from YouTube and various film clips. This will provide us with practical and varied scenarios of road conditions, enhancing the realism and applicability of our models.

**1.3.2 Collaborations and Dependencies:**

Our project's success hinges on collaborative engagements and interactions with various external entities, each offering unique contributions and resources.

1. **Valeo (Project Sponsor):** Regular interactions with Valeo are essential for tracking project progress and ensuring alignment with their expectations. These communications provide us with valuable feedback, guiding adjustments and ensuring the project meets Valeo's requirements. Valeo's involvement is a key dependency for project guidance and validation.
2. **Mentors from the University of Ottawa:** Biweekly meetings with our Ottawa-based mentor, a cornerstone for scientific guidance, offer academic expertise and insights. This mentorship is critical for enhancing the project's scientific rigor and implementation strategy. The mentor's availability and input are crucial for our project's technical and theoretical development.
3. **DEBI (Regulatory and Technical Mentor):** Our collaboration with Debi mentor focuses on gaining insights into regulatory compliance and technical best practices. Regular interactions through meetings, emails, and face-to-face engagements are pivotal for aligning our project with industry standards and technical requirements. Debi's expertise and availability are key dependencies for ensuring the project's adherence to regulatory norms and technical excellence.
4. **Data Contributors:** Individuals from regions prone to road hazards provide us with high-quality videos and images on YouTube and similar open-source platforms, enriching our dataset with real-world scenarios. Their contributions are invaluable for robust data analysis and the effectiveness of our models. Ensuring their continued participation and access to their data is a critical dependency.
5. **Researchers and Authors:** We seek to interact with researchers and authors of referenced papers to access specific data used in their studies. While efforts to obtain this data are ongoing, their cooperation and willingness to share information are key dependencies that could significantly impact the depth and quality of our research.

**1.3.3 Availability and Accessibility:**

Confirming the availability and accessibility of these external entities and resources is a priority. Regular communication channels have been established with Valeo, our mentors, and data contributors to ensure consistent engagement and support. For researchers and authors, we maintain continuous communication to potentially secure access to their data. The success of our project relies heavily on these collaborations and the timely availability of the resources and expertise they provide.

A screenshot of a computer screen

Description automatically generated**2. Design Overview**

Figure 1: Solution Design Diagram

**2.1 Requirements**

The development of our road hazard detection system is driven by a set of comprehensive and detailed requirements that ensure its effectiveness and practicality.

**These requirements include**:

1. **Accuracy:** High precision in detecting and classifying road hazards, minimizing false positives and negatives.
2. **Real-time Performance:** The system must operate in real-time for prompt hazard alerts.
3. **Robustness:** Ability to perform under various environmental conditions.
4. **User-Friendly Interface:** Intuitive interface for easy image or video input.
5. **Scalability:** Potential for future enhancements and additional hazard detection features.
6. **Adaptability:** Compatibility with various vehicle types and models.
7. **Data Privacy and Security:** Ensuring the protection of user data.
8. **Reliability:** Consistent performance under challenging conditions.
9. **Scalable Training and Deployment:** Efficient utilization of resources for training and deployment on different hardware.
10. **Continuous Improvement and Updates:** Support for incorporating new algorithms and datasets.
11. **Integration with Vehicle Systems:** Compatibility with existing vehicle safety systems.
12. **Validation and Performance Metrics:** Rigorous testing using accuracy, precision, recall, and other metrics.
13. **Defense against Adversarial Attacks:** Techniques to maintain robustness against manipulation.

**2.2 Detailed Design**

The system is designed with several key components interacting to achieve the desired functionality:

* **Data Collection:** Utilizing diverse sources like YouTube, Roboflow, and Google Images to compile a comprehensive dataset.
* **Data Cleaning and Labeling**: Videos underwent cleaning to discard irrelevant frames. The remaining frames were manually labeled into three classes: clear, snow, and ice. In refinement, "ice" became "snow-ice" for improved road condition representation.
* **Data Preprocessing:** Before training the models, various preprocessing techniques were applied to the labeled data. This included resizing the images to a standardized dimension and normalizing the pixel values to enhance model performance.
* **Train-Test Split and Data Augmentation:** Data was split into an 80-20 train-test ratio, ensuring the test set remained untouched to prevent data leakage. Training data was augmented using techniques like rotation, flipping, and zooming for increased diversity.
* **Model Training**: Utilizing a range of deep learning models, including VGG, ResNet, and Inception, to identify the most effective solution for hazard detection.
* **Model Evaluation:** Assessing models using metrics like accuracy, precision, recall and f1 score to identify the best-performing model.
* **Hyperparameter Tuning:** Optimizing the model for better performance.
* **Application Development:** Creating a desktop application that is both functional and user-friendly, facilitating Valeo sponsors in testing the model.

The system's design ensures seamless interaction and data flow between these components.

**2.3 Implementation**

* The final implementation of the project successfully met all outlined requirements:
* **Software Integration:** The system integrates Python, OpenCV, TensorFlow, and Tkinter, ensuring efficient data processing and user interaction.
* **Model Development:** The implementation of CNN architectures using TensorFlow provided robust hazard detection capabilities.
* **GUI Development:** Tkinter was employed to develop a user-friendly interface for real-time.
* hazard visualization and interaction, enhancing the overall user experience.
* A blue squares with white text

  Description automatically generated**Experimental Setup and Evaluation:** The system was rigorously tested with a diverse dataset, undergoing preprocessing and model training, and evaluated using precision, recall, and F1-score metrics.

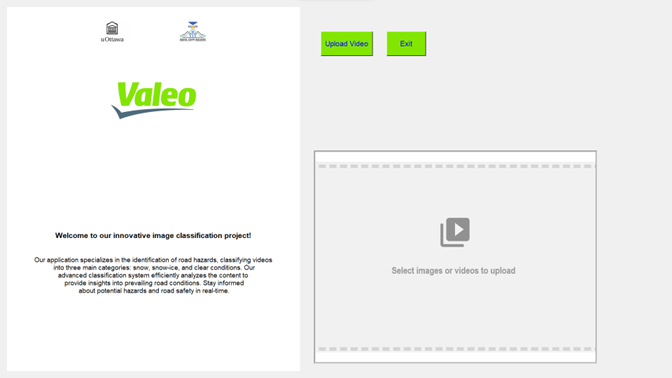
****Figure 2: Confusion Matrix for Best Implementation Model

Figure 3: final project implementation

**2.4 Testing**

**2.4.1 Data Plan**

* **Data Sources**: we collected images from Google Images, Roboflow, and YouTube videos, to ensure a rich and varied dataset.
* **Data Extraction and Labeling:** Each image was carefully labeled according to its corresponding hazard class after being extracted from YouTube videos. The dataset was then cleansed to remove any irrelevant or mislabeled samples, ensuring data integrity and relevance.
* **Data Organization:** The dataset was methodically organized into specific folders based on hazard classes, facilitating efficient access and management during the training and testing phases.
* **Data Preprocessing:** OpenCV was used for image resizing and normalization, preparing the data for model training.
* A screenshot of a computer

  Description automatically generated**Model Training and Evaluation:** Models were trained using TensorFlow on the annotated dataset, focusing on their accuracy and generalization capabilities.

Figure 4: Data Labels

**2.4.2 Validation & Verification**

In the validation and verification phase of our road hazard detection project, a high priority was placed on achieving a high recall rate, especially for the 'clear' road condition (Class 0), to minimize false negatives. Extensive testing procedures were employed, using a mix of real-world and simulated data, ensuring the system's robustness across various scenarios. Continuous analysis of the modeling results, with a focus on metrics like recall, precision, accuracy, and F1 score, led to the selection and refinement of the VGG16 model. We conducted routine repetitive testing to ensure the model's reliability and consistency over time, adapting to new data and environmental changes. Operational needs and user feedback were crucial in simulating driving scenarios and refining the user interface. Predictive simulations for fault and gap analysis were instrumental in identifying and addressing potential system weaknesses. By tuning hyperparameters and adjusting the model to focus primarily on the road, we enhanced its accuracy in distinguishing between 'clear', 'snow', and 'snow-ice' conditions. The final integration of the model into a user-friendly interface using Tkinter made the system not only highly effective in hazard detection but also practical and accessible for end-users, marking a significant advancement in AI applications for road safety.

**3. Overall Results and Analysis**

**Model Performance Assessment:**

The project's comprehensive evaluation highlighted the distinguishing capabilities of the selected machine learning models. The calculated performance metrics precision, recall, and F1-score for each model provided an insightful assessment of their predictive accuracy.

**Detailed Observations from Model Performance:**

* **ResNet50 Model:** The performance of ResNet50 was notably lower than anticipated, particularly in identifying 'Snow' and 'Snow-Ice' classes. The confusion matrix indicated 'Clear' conditions and an inability to recognize the other two conditions.
* **InceptionV3 Model:** InceptionV3 demonstrated exemplary performance. The confusion matrix displayed a high level of accuracy, with an almost flawless prediction rate for 'Clear' conditions and substantial accuracy for 'Snow' and 'Snow-Ice' classes.
* **VGG16 Model:** The confusion matrix for VGG16 showed remarkable recall across all categories. Its ability to accurately classify almost every instance makes it a highly reliable model for practical deployment.

**Comparative Analysis Based on F1-Scores:**

A table summarizing the F1-scores for each model would typically be presented here to provide a concise comparison of their performances.

|  |  |  |  |
| --- | --- | --- | --- |
| **Model** | **Clear** | **Snow** | **Snow-Ice** |
| **ResNet50** | 0.71 | 0.24 | 0.00 |
| **InceptionV3** | 1.0 | 0.95 | 0.93 |
| **VGG16** | 1.0 | 0.98 | 0.97 |

Table 1: Comparative Analysis Based on F1-Scores

**Reflections on the Project's Process:**

* The disparity in model performances underscored the criticality of tailored model selection for specific datasets in machine learning endeavors.
* Adjustments to the ResNet50 model, informed by its confusion matrix results, point towards an iterative development approach that could streamline future projects.

**Contribution to Academic** and **Professional Growth:**

* The project's challenges and successes contributed significantly to the practical learning outcomes associated with our graduate program in AI and Data Science.
* The experience has refined our ability to critically assess machine learning models and will undoubtedly benefit our career in AI research and development.

**Overall Project Success:**

* Despite ResNet50's unexpected underperformance, the project met its goals with the high accuracy of InceptionV3 and VGG16 models.
* The confusion matrices for these models would be placed here for visual reference and further observation.

**ResNet50 Confusion Matrix:**

A blue and white chart with numbers and text

Description automatically generated with medium confidence

Figure 5: ResNet50 Confusion Matrix

**InceptionV3 Confusion Matrix:**

A blue squares with white text

Description automatically generated

Figure 6: InceptionV3 Confusion Matrix

**VGG16 Confusion Matrix:**

A blue squares with white text

Description automatically generated

Figure 7: VGG16 Confusion Matrix

The project's outcomes have not only demonstrated success in meeting its objectives but have also laid a solid foundation for the advancement of road hazard detection technologies.

**4. Deployment Plan**

The deployment plan for our road hazard detection system involves the seamless integration of our trained model into user-friendly interfaces for both web-based and desktop applications. To cater to a diverse range of users, we have adopted a dual approach, utilizing StreamLit for web deployment and Tkinter for a desktop application.

For the web-based solution, we chose StreamLit, a powerful Python framework that facilitates the creation of interactive data applications with minimal effort. Our StreamLit app enables users to upload images directly through a user-friendly interface. Once the image is uploaded, the system utilizes our pre-trained model to classify road hazards, providing immediate results on the screen. This approach ensures a straightforward and efficient user experience, allowing users to leverage our solution effortlessly.

To extend accessibility and accommodate users preferring a desktop application, we have developed a Graphical User Interface (GUI) using Tkinter, a standard Python library for creating desktop applications. The Tkinter-based desktop application encapsulates the functionality of our road hazard detection system. Utilizing PyInstaller, we convert the Tkinter script into a standalone executable, eliminating the need for users to navigate through complex installation processes.

In both instances, our deployment plan prioritizes user-friendliness and simplicity. The web-based application hosted on StreamLit allows users to access the system through a standard web browser, while the desktop application provides a standalone solution for users who prefer a more integrated experience. By adopting these approaches, we aim to enhance the accessibility of our road hazard detection system, ensuring a smooth end-user experience. Additionally, we remain committed to addressing maintainability issues and providing comprehensive documentation to facilitate users in leveraging our solution effectively in diverse operational environments.

A screenshot of a computer

Description automatically generated

Figure 8: Streamlit testing

**A screenshot of a web page

Description automatically generated**

Figure 9: Application testing

**5. Conclusions and Future Works**

The project has not only met its goals but has also set the stage for further advancements in road hazard detection technologies. Despite challenges, the high accuracy of the InceptionV3 and VGG16 models has underscored the success of the project, showcasing its potential to enhance road safety significantly. Our comprehensive literature review has not only shaped our current approach but has also laid the groundwork for future innovations in the field of road safety and hazard detection. The experience gained from this project has significantly contributed toour practical learning outcomes in AI and Data Science, refining our ability to critically assess machine learning models and enhancing our potential in AI research and development. Our deployment plan prioritizes user-friendliness and accessibility, ensuring that our road hazard detection system can be effectively utilized in diverse operational environments. As we move forward, the success and insights from this project will continue to guide our development, setting the stage for further innovation and impact in the field of road safety.

In the future work section, we should highlight potential areas for improvement and expansion based on the project's status. Leveraging the requirements outlined for the road hazard detection system, the future work can involve discussions on how to further enhance the system. This could include:

**1. Enhanced Hazard Classification:** Further refinement of the classification models to differentiate between specific types of road hazards, such as distinguishing between different levels of snow or ice accumulation.

**2. Integration of Sensor Data:** Exploring the integration of additional sensor data, such as radar or LiDAR, to complement visual hazard detection, thereby enhancing the system's robustness and accuracy.

**3. Adaptation for Autonomous Vehicles:** Investigating how the system can be adapted for seamless integration with autonomous vehicle platforms, ensuring compatibility with advanced driving assistance systems (ADAS) and autonomous driving functions.

**4. Privacy and Security Enhancements:** Continuously enhancing data privacy and security measures to maintain the protection of user data and ensure compliance with evolving regulations.

**5. Diversified Hazard Detection:** Expanding the system's capabilities to detect a broader spectrum of road hazards, such as mud, debris, and other obstructions, fostering a more comprehensive approach to road safety.

**6.** **Thermal Imaging for Black Ice Detection**: Exploring the integration of thermal imaging technology for the specific detection of black ice hazards, leveraging advanced image processing and machine learning techniques for real-time identification in diverse environmental conditions.

These potential areas for future work are grounded in the project's current requirements and reflect opportunities for further innovation and impact in road hazard detection.

**6. References**

[1] Habib Tabatabai and Mohammed Aljuboori. “A Novel Concrete-Based Sensor for Detection of  
Ice and Water on Roads and Bridges”. In: Sensors 17.12 (Dec. 2017), p. 2912. issn: 1424-8220.  
doi: 10.3390/s17122912. url: <http://dx.doi.org/10.3390/s17122912>.

[2] Younis E. Abdalla, M. Tariq Iqbal, and Mohamed S. Shehata. “Black Ice detection system  
using Kinect”. In: 2017 IEEE 30th Canadian Conference on Electrical and Computer Engi-  
neering (CCECE) (2017), pp. 1–4. url: <https://api.semanticscholar.org/CorpusID:38343478>.

[3] Lushan Cheng, Xu Zhang, and Jie Shen. “Road surface condition classification using deep  
learning”. In: Journal of Visual Communication and Image Representation 64 (2019), p. 102638.  
issn: 1047-3203. doi: https://doi.org/10.1016/j.jvcir.2019.102638. url: <https://www.sciencedirect.com/science/article/pii/S1047320319302597>.

[4] Xinxu Ma and Chi Ruan. “Method for black ice detection on roads using triwavelength  
backscattering measurements”. In: Applied Optics 59 (July 2020). doi: 10.1364/AO.398772.

[5] HoJun Lee et al. “Black ice detection using CNN for the Prevention of Accidents in Automated  
Vehicle”. In: (2020), pp. 1189–1192. doi: 10.1109/CSCI51800.2020.00222.

[6] Guangyuan Pan et al. “Real-time winter road surface condition monitoring using an improved  
residual CNN”. In: Canadian Journal of Civil Engineering 48.9 (2021), pp. 1215–1222. doi:  
10.1139/cjce- 2019- 0367. eprint: https://doi.org/10.1139/cjce- 2019- 0367. url:  
<https://doi.org/10.1139/cjce-2019-0367>.

[7] Ce Zhang et al. “Winter road surface condition classification using convolutional neural net-  
work (CNN): visible light and thermal image fusion”. In: Canadian Journal of Civil Engineer-  
ing 49.4 (2022), pp. 569–578. doi: 10.1139/cjce-2020-0613. eprint: <https://doi.org/10.1139/cjce-2020-0613>.url: <https://doi.org/10.1139/cjce-2020-0613>.

[8] Yanan Xu et al. “Intelligent Black Ice Detection and Alert System Using Thermal Imaging  
Camera and Drone”. In: (2021), pp. 2328–2331. doi: 10.1109/HPCC-DSS-SmartCity-DependSys53884.2021.00351