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# BSc (Hons) in Information Technology Specializing Data Science

## Research Project - IT4010 Ethical Analysis Report

Group ID: 24_25J_213

Project Title: ManthraX: Pioneering Precision, The Future of autonomous Mobility

IT21160448: Perception and Scene Understanding

| | **Identification and Analysis** |
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| **Data Privacy Concerns** | •YOLOv5 for Object Detection: The model processes simulated images from the CARLA simulator, which means there is no real-world data involved, and thus no direct privacy concerns individuals. However, if the model is later deployed in real-world scenarios, privacy concerns (e.g., anonymizing faces or license plates) will need to be addressed.<br>•CNN Based Lane Keeping Model: Similarly, the model uses simulated images from the CARLA simulator, so there are no immediate privacy concerns. However, future real-world deployments will require anonymization of sensitive information in the images.<br>•GNN With Transformer – Behavior Classification: The model collects data from the CARLA simulator, including the behavior of surrounding vehicles. While the data is simulated, it is essential to ensure that any real-world data used in the future is anonymized and collected with informed consent. |
| **Data Security** | •YOLOv5 for Object Detection: While the data is simulated, the model's weights, training data, and inference results should still be stored securely to prevent unauthorized access or tampering. This is especially important if the model is later adapted for real-world use.<br>•CNN Based Lane Keeping Model: The simulated images and steering angle data should be stored securely, with access controls in place to prevent unauthorized access. This ensures that the model's integrity is maintained, even in a simulated environment.<br>•GNN With Transformer – Behavior Classification: The temporal graph data should be encrypted, and secure access protocols should be implemented to protect the data from breaches. |
| **Bias and Fairness** | •YOLOv5 for Object Detection: The model may exhibit biases if the simulated dataset does not accurately represent real-world diversity (e.g., different types of vehicles, pedestrians, or road conditions). Regular audits of the dataset and model performance are necessary to ensure fairness, especially if the model is later deployed in real-world scenarios.<br>•CNN Based Lane Keeping Model: The model's performance may vary based on the diversity of the simulated road conditions (e.g., poorly marked lanes, different lighting conditions). Ensuring a diverse and representative training dataset is crucial to avoid biased predictions.<br>•GNN With Transformer – Behavior Classification: The model may exhibit biases if the simulated data does not accurately represent real-world scenarios. Regular testing with diverse scenarios is necessary to ensure fairness. |

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| **Transparency and Accountability** | •YOLOv5 for Object Detection: The model's decision-making process should be transparent, with clear documentation of how objects are detected and classified. Even though the data is simulated, the team should be accountable for any errors or accidents caused by the model in the simulation.<br>•CNN Based Lane Keeping Model: The model's architecture and training process should be well-documented, and the team should be accountable for any steering errors in the simulation. Transparency in how the model predicts steering angles is essential for trust and reliability.<br>•GNN With Transformer – Behavior Classification: The model's behavior classification process should be transparent, with clear documentation of how vehicle behaviors are predicted. The team should be accountable for any incorrect predictions. |
| **Impact on Stakeholders** | •YOLOv5 for Object Detection: While the model is currently used in a simulated environment, its outcomes could impact the safety of passengers and other road users if deployed in real-world scenarios. Incorrect object detection in the simulation could lead to unsafe driving behaviors, which must be addressed before real-world deployment.<br>•CNN Based Lane Keeping Model: Incorrect steering predictions in the simulation could lead to unsafe driving behaviors, affecting the safety of passengers and other road users. Ensuring the model's reliability in the simulation is crucial before transitioning to real-world applications.<br>•GNN With Transformer – Behavior Classification: Incorrect behavior classification could lead to unsafe driving decisions, affecting the safety of passengers and other road users. This is especially critical in real-world scenarios, where incorrect predictions could result in accidents. |

IT21155048: Decision Making and Collison Avoidance

| | Identification and Analysis |
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| **Data Privacy Concerns** | •Collision Avoidance: The model processes simulated data from the CARLA simulator, including the behavior of surrounding vehicles. Since the data is simulated, there are no immediate privacy concerns related to real-world individuals. However, if the model is later deployed in real-world scenarios, privacy concerns (e.g., anonymizing vehicle or pedestrian data) will need to be addressed.<br>•Decision Making: Similarly, the model uses simulated data from the CARLA simulator, so there are no direct privacy concerns. However, future real-world deployments will require anonymization of sensitive information, such as vehicle or pedestrian identities. |
| **Data Security** | •Collision Avoidance: The temporal graph data and model weights should be stored securely to prevent unauthorized access or tampering. This is especially important if the model is later adapted for real-world use.<br>• Decision Making: The data used for training and inference should be stored securely, with access controls in place to prevent unauthorized access. This ensures that the model's integrity is maintained, even in a simulated environment. |
| **Bias and Fairness** | •Collision Avoidance: The model may exhibit biases if the simulated dataset does not accurately represent real-world diversity such as different types of vehicles, pedestrians, or traffic scenarios. Regular audits of the dataset and model performance are necessary to ensure fairness, especially if the model is later deployed in real-world scenarios.<br>• Decision Making: The model's performance may vary based on the complexity of traffic scenarios in the simulation. Ensuring a diverse and representative training dataset is crucial to avoid biased predictions, particularly in edge cases such as sudden pedestrian crossings or vehicles ignoring traffic signals. |
| **Transparency and Accountability** | •Collision Avoidance: The model's behavior classification process should be transparent, with clear documentation of how vehicle behaviors are predicted.<br>• Decision Making: The model's decision-making process should be transparent, with clear documentation of how collision avoidance decisions are made. The team should be accountable for any errors or accidents caused by the model in the simulation. |
| **Impact on Stakeholders** | •Collision Avoidance: While the model is currently used in a simulated environment, its outcomes could impact on the safety of passengers and other road users if deployed in real-world scenarios. Incorrect |

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| | behavior classification could lead to unsafe driving decisions, which must be addressed before real-world deployment.<br>• Decision Making: Incorrect collision avoidance decisions in the simulation could lead to unsafe driving behaviors, affecting the safety of passengers and other road users. Ensuring the model's reliability in the simulation is crucial before transitioning to real-world applications. |

IT21162978: Driver Monitoring and Ethical Decision-Making

| | Identification and Analysis |
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| **Data Privacy Concerns** | •Eyeball Tracking System: The model processes real-world data from drivers, including facial features, eye movements, and gaze direction. This data is highly sensitive, as it can reveal personal information about the driver. Ensuring that the data is anonymized such as blurring faces or removing identifiable features is crucial to protect the privacy of individuals.<br>•Ethical Decision Making: The model processes simulated data from the CARLA simulator, including vehicle positions, pedestrian movements, and traffic scenarios. While the data is simulated, any real-world data used in the future must be anonymized and collected with informed consent. |
| **Data Security** | •Eyeball Tracking System: The real-world data collected from drivers must be stored securely, with robust encryption and access controls in place to prevent unauthorized access or misuse. This is especially important given the sensitive nature of the data.<br>•Ethical Decision Making: The simulated data and model weights should be stored securely to prevent unauthorized access or tampering. This is especially important if the model is later adapted for real-world use. |
| **Bias and Fairness** | •Eyeball Tracking System: The model may exhibit biases if the training dataset does not accurately represent diverse driver populations (e.g., different ethnicities, ages, or genders). Regular audits of the dataset and model performance are necessary to ensure fairness, especially in real-world deployments.<br>•Ethical Decision Making: The model may exhibit biases if the simulated data does not accurately represent real-world ethical dilemmas. Regular testing with diverse scenarios is necessary to ensure fairness, especially if the model is later deployed in real-world scenarios. |
| **Transparency and Accountability** | •Eyeball Tracking System: The model's decision-making process should be transparent, with clear documentation of how eye movements and gaze direction are tracked and interpreted. The team should be accountable for any errors or false alerts generated by the system.<br>•Ethical Decision Making: The model's decision-making process should be transparent, with clear documentation of how ethical decisions are made. The team should be accountable for any unethical decisions made by the model, especially in high-risk scenarios. |
| **Impact on Stakeholders** | •Eyeball Tracking System: The model's outcomes directly impact the safety of drivers and passengers. Incorrect tracking of eye movements or gaze direction could lead to false alerts or missed warnings, affecting the driver's ability to respond to road conditions.<br>•Ethical Decision Making: The model's outcomes directly impact the safety of passengers, pedestrians, and other road users. Unethical decisions could lead to accidents, affecting the autonomy and rights of individuals. |

IT21174780: In Cabin Security in Autonomous Vehicles

| | Identification and Analysis |
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| **Data Privacy Concerns** | •Emotion Detection: The model processes real-world facial images to classify emotions. This data is highly sensitive, as it can reveal personal information about individuals. Ensuring that the data is anonymized (e.g., blurring faces or removing identifiable features) is crucial to protect privacy.<br>•Harmful Status Detection: The model processes real-world audio data to classify harmful statuses (e.g., glass breaking). While audio data is less visually identifiable, it may still contain sensitive information (e.g., voices or background conversations). Anonymization and secure handling of this data are necessary.<br>•Weapon Detection with YOLOv8: The model processes real-world images to detect weapons. These images may include sensitive information about individuals or locations. Ensuring that the data is anonymized (e.g., blurring faces or license plates) is crucial to protect privacy. |
| **Data Security** | •Emotion Detection: The real-world facial images must be stored securely, with robust encryption and access controls in place to prevent unauthorized access or misuse. This is especially important given the sensitive nature of the data.<br>•Harmful Status Detection: The real-world audio data must be stored securely, with encryption and access controls to prevent unauthorized access. This ensures that sensitive information is protected.<br>•Weapon Detection with YOLOv8: The real-world images must be stored securely, with robust encryption and access controls to prevent unauthorized access or misuse. This is especially important given the sensitive nature of the data. |
| **Bias and Fairness** | •Emotion Detection: The model may exhibit biases if the training dataset does not accurately represent diverse populations (e.g., different ethnicities, ages, or genders). Regular audits of the dataset and model performance are necessary to ensure fairness.<br>•Harmful Status Detection: The model may exhibit biases if the training dataset does not accurately represent diverse audio scenarios (e.g., different types of harmful sounds or background noise). Regular audits of the dataset and model performance are necessary to ensure fairness.<br>•Weapon Detection with YOLOv8: The model may exhibit biases if the training dataset does not accurately represent diverse scenarios (e.g., different types of weapons, lighting conditions, or environments). Regular audits of the dataset and model performance are necessary to ensure fairness. |
| **Transparency and Accountability** | •Emotion Detection: The model's decision-making process should be transparent, with clear documentation of how emotions are classified. The team should be accountable for any errors or misclassifications.<br>•Harmful Status Detection: The model's decision-making process should be transparent, with clear documentation of how harmful statuses are classified. The team should be accountable for any errors or false positives/negatives.<br>•Weapon Detection with YOLOv8: The model's decision-making process should be transparent, with clear documentation of how weapons are detected. The team should be accountable for any errors or false detections. |

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| **Impact on Stakeholders** | •Emotion Detection: The model's outcomes could impact individuals' privacy and autonomy if misused. Incorrect emotion classification could lead to inappropriate responses or decisions, affecting individuals' rights.<br>•Harmful Status Detection: The model's outcomes could impact individuals' safety and privacy. Incorrect classification of harmful statuses could lead to false alarms or missed threats, affecting individuals' safety.<br>•Weapon Detection with YOLOv8: The model's outcomes could impact public safety and individual rights. Incorrect weapon detection could lead to false accusations or missed threats, affecting individuals' safety and rights. |