# REAL TIME XAI FOR AUTONOMOUS VEHICHES DECISIONS MAKING

**BY**

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## CERTIFICATION

This is to certify that this project work was carried out by OWATIMEHIN JUSTINAH MARY of the department of computer science of Benson Idahosa University Benin city, Edo State, Nigeria in partial fulfilment of the requirements for the award of the master of Computer Science (MSC) degree in computer.

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## DEDICATION

This project is lovingly dedicated to my daughters, whose love, patience, and understanding have been a constant source of strength and inspiration throughout my academics journey. Your encouragement, prayers, and sacrifices gave me the motivation to persevere and successfully complete this programme.

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## ABSTRACT

This study focused on the development of a Real-Time Explainable Artificial Intelligence (XAI) decision support system for autonomous vehicle decision-making. The study addressed the need for transparent, safe, and interpretable driving decisions because conventional deeplearning systems can operate as black boxes. The proposed system adopted a hybrid Convolutional Neural Network (CNN) and Transformer architecture. The CNN component was designed to extract local patterns from driving inputs, while the Transformer component captured broader contextual and temporal relationships through attention mechanisms. A decision support module generated driving actions such as BRAKE, SLOW DOWN, and MAINTAIN SPEED, while the XAI component provided human-understandable explanations of the factors influencing each decision. The system was evaluated in a simulation environment using vehicle speed, road-risk level, obstacle status, confidence, and explanation outputs. The implementation used Python for model development, data processing and visualization, together with web technologies and MySQL for system interaction and data management. The simulation covered 50 time steps, with vehicle speed ranging from approximately 32 km/h to 98 km/h and road-risk values from 0.05 to 0.95. The observed decision distribution remained safety-oriented, with BRAKE, SLOW DOWN, and MAINTAIN SPEED actions generated under high-, moderate-, and low-risk conditions respectively. The study demonstrates how a CNN-Transformer decision support architecture can provide a structured basis for real-time autonomous driving decisions while improving interpretability through attention-based and feature-level explanations. The work is intended as a simulation-based research prototype rather than a deployment on a physical autonomous vehicle.

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# CHAPTER ONE

# INTRODUCTION

## 1.1 Background to the Study

Autonomous vehicles (AVs) have emerged as one of the most transformative innovations in modern transportation systems, driven by rapid advancements in Artificial Intelligence (AI), machine learning, and intelligent control systems. These vehicles are designed to perceive their surroundings, interpret complex traffic environments, and make real-time driving decisions such as braking, steering, lane changing, acceleration, and obstacle avoidance. According to Stanton *et al*. (2021), autonomous systems rely heavily on advanced machine learning algorithms that process large-scale, high-dimensional data collected from multiple onboard sensors including cameras, LiDAR, radar, and GPS. These sensor technologies collectively enable vehicles to construct a detailed and continuous understanding of their environment, thereby supporting intelligent navigation in highly dynamic and unpredictable traffic conditions.

Furthermore, Yurtsever*et al.* (2020) emphasized that the integration of sensor fusion and deep learning techniques has significantly improved the perception capabilities of autonomous vehicles, allowing them to detect objects, classify road users, and predict motion trajectories with high accuracy. However, despite these advancements, the decision-making processes of many autonomous systems remain difficult to interpret due to the complexity of the underlying models.

Despite the remarkable progress achieved in autonomous driving technologies, a major limitation remains the lack of transparency in how AI systems make decisions. Most modern autonomous vehicle models operate as black-box systems, meaning that although they can generate highly accurate predictions and decisions, they do not provide clear explanations of how or why those decisions were made (Yurtsever*et al*., 2020). This lack of interpretability presents a serious challenge, especially in scenarios involving unexpected road events, nearcollision situations, or adverse weather conditions where understanding the system's reasoning
is critical.

The absence of explainability in autonomous vehicle decision-making has raised significant concerns regarding safety, accountability, ethics, and public trust. In safety-critical domains such as transportation, any incorrect or unexplained decision can result in severe consequences, including road accidents, legal disputes, and reduced user acceptance of autonomous systems. Selvaraju*et al*. (2020) noted that the inability to interpret AI decision-making processes limits debugging, system validation, and regulatory approval, thereby hindering large-scale deployment of autonomous technologies in real-world environments. Consequently, there has been a growing demand from stakeholders—including governments, manufacturers, engineers, and end-users—for AI systems that are not only accurate but also transparent, interpretable, and accountable.

In response to these challenges, Explainable Artificial Intelligence (XAI) has emerged as a critical research domain aimed at improving the interpretability of AI systems. XAI focuses on developing methods that provide human-understandable explanations for model predictions and decisions, thereby enabling users to understand how inputs influence outputs. In the context of autonomous vehicles, XAI plays an essential role in enhancing system reliability, supporting fault diagnosis, identifying potential model biases, and ensuring compliance with safety regulations and ethical standards. Samek*et al*. (2019) highlighted that XAI bridges the gap between complex machine learning models and human interpretability by transforming abstract model behavior into meaningful explanations.

In recent years, real-time Explainable Artificial Intelligence has gained increasing attention, particularly in autonomous driving systems where decisions must be made within milliseconds under dynamic and uncertain conditions. Unlike traditional post-hoc explanation approaches that analyze decisions after they have occurred, real-time XAI generates explanations simultaneously with decision-making processes. This ensures that interpretability does not compromise system responsiveness or safety. Atakishiyev*et al*. (2021) emphasized that realtime explainability enhances accountability, improves system transparency, and increases user trust by allowing continuous insight into AI-driven decisions as they are being made.

Additionally, Ribeiro *et al*. (2016) introduced model-agnostic interpretability methods such as LIME, which demonstrated that even complex machine learning models could be explained locally through simplified surrogate models. Similarly, Selvaraju*et al*. (2017) proposed GradCAM, a visualization-based technique that highlights important regions influencing deep learning decisions, which has become widely used in computer vision applications, including autonomous driving perception systems.

Building upon these advancements, the proposed system integrates CNN-based feature extraction, Transformer-based contextual modelling, decision support, and real-time explainability into a single autonomous vehicle research pipeline. The design aims to make the relationship between driving inputs, model decisions, and explanations visible to users and developers.

The development of real-time XAI-based autonomous systems represents a significant step toward safer, more accountable, and socially acceptable intelligent transportation systems.

### 1.2 Statement of the Problem

Despite advances in autonomous vehicle technology and the emergence of explainable AI, many autonomous-driving decision models remain difficult to interpret, particularly when complex visual and temporal information is processed by deep neural networks. Existing research has demonstrated Transformer-based systems that can generate driving actions together with explanations, but there remains a need for decision-support architectures that combine local feature extraction, global contextual modelling, vehicle-state information, and an accessible real-time explanation interface. The absence of such an integrated prototype can limit practical evaluation, debugging, and understanding of model behaviour in simulation-based autonomous driving research.

### 1.3 Aim and Objectives of the Study

The study aims to develop a Real-Time Explainable Artificial Intelligence decision support system for autonomous vehicle decision-making using a hybrid CNN-Transformer architecture. The study objectives are to;

i. i. Design and implement a hybrid CNN-Transformer decision support model for autonomous vehicle driving decisions using environmental and vehicle-state parameters.

ii. Develop an explainability component that provides clear and human-understandable reasons for decisions such as braking, slowing down, and maintaining speed.

iii. Implement a web-based interface using HTML, CSS, JavaScript, PHP, and MySQL to display system inputs, decisions, explanations, and evaluation results.

iv. Evaluate the relationship between driving conditions, model decisions, confidence levels, and explanation outputs in a simulation environment.

**1.4 Significance of the Study**

This study contributes to both theory and practice. Academically, it advances knowledge on integrating XAI into safety-critical systems. Practically, it supports the development of AVs that are transparent, trustworthy, and socially acceptable, addressing ethical and regulatory concerns. The outcomes will benefit manufacturers, policymakers, and end-users by promoting safer and more explainable autonomous driving technologies.

**1.5 Scope of the Study**

The study evaluates the proposed CNN-Transformer decision support system based on decision performance, explanation quality, computational behaviour, and interpretability. Testing and validation are conducted primarily in a simulation environment. Field deployment on live traffic and physical autonomous vehicles remains outside the scope because of safety, hardware, and regulatory constraints.

**1.6 Limitations of the Study**

The study will be subject to the following limitations:

i. The evaluation relies primarily on simulated driving data, which may not fully represent the complexity and variability of real-world autonomous driving conditions.

ii. The evaluation will be conducted in a simulated environment rather than on physical autonomous vehicles.

iii. Computational and hardware constraints may limit real-time explanation speed and scalability.

iv. Only selected XAI techniques will be considered, excluding other advanced explainability approaches.

v. The client–server architecture will assume stable network connectivity, which may not reflect real-world communication challenges.

vi. Human-centered evaluation of explanations and user trust assessment will not be extensively covered

## 1.7 Definition of Terms

**Autonomous Vehicle (AV):** A self-driving vehicle that was designed to sense its environment and operate without human intervention.

**Artificial Intelligence (AI):** A branch of computer science that enabled machines to simulate human intelligence such as learning, reasoning, and decision-making.

**Explainable Artificial Intelligence (XAI):** A type of AI that provided clear and understandable explanations for the decisions made by machine learning models.

**Machine Learning:** A subset of AI that allowed systems to learn patterns from data and improve performance without being explicitly programmed.

**Black-Box Model:** An AI system whose internal decision-making process was not easily understandable by humans.

**Sensor Fusion:** The process of combining data from multiple sensors such as cameras, radar, and LiDAR to improve system accuracy.

**LiDAR:** A sensing technology that used laser light to measure distances and create 3D maps of the environment.

**Radar:** A detection system that used radio waves to determine the position and speed of objects.

**Real-Time Processing:** The ability of a system to process data and make decisions instantly without delay.

**Decision-Making System:** A computational system that analyzed input data and selected appropriate actions such as braking or steering.

**Obstacle Avoidance:** The ability of a vehicle to detect and avoid collisions with objects in its environment.

**Interpretability:** The degree to which a human can understand how an AI system arrived at a decision.

**Confidence Level:** A numerical value that represented how certain the AI system was about its decision.

Convolutional Neural Network (CNN): A deep-learning architecture that uses convolutional operations to extract local patterns and hierarchical features from structured inputs such as images or sequences. Transformer: A neural-network architecture based on attention mechanisms that models relationships among input elements and is useful for capturing contextual and long-range dependencies.

# CHAPTER TWO

# LITERATURE REVIEW

## 2.1 Autonomous Vehicles (AVs)

Autonomous Vehicles (AVs) are vehicles that are capable of navigating and performing driving tasks without direct human intervention, using a combination of sensors, actuators, and intelligent algorithms. AVs rely on sensors such as cameras, LiDAR, radar, ultrasonic sensors, and GPS to perceive their surrounding environment, including other vehicles, pedestrians, traffic signs, road lanes, and obstacles. These data are continuously processed to make critical driving decisions such as steering, acceleration, braking, and lane changes in real time.

AVs are typically classified into six levels of automation, from Level 0 (no automation) to Level 5 (full automation), as defined by SAE International (2021). The higher levels of automation require sophisticated decision-making systems capable of handling complex and dynamic traffic scenarios. Despite their potential to reduce human error, improve traffic efficiency, and increase mobility accessibility, AVs face challenges in safety assurance, accountability, and public acceptance due to the opacity of their decision-making processes (Kockelman, 2021).

the real-world deployment of AVs requires the integration of advanced communication systems, such as vehicle-to-vehicle (V2V) and vehicle-to-infrastructure (V2I) networks, to enhance situational awareness and coordinate driving decisions among multiple vehicles in traffic environments. These technological dependencies further highlight the need for transparent, explainable, and accountable autonomous systems (Shalev-Shwartz*et al.,* 2022).

## 2.2 Related works

Explainable Artificial Intelligence research by Kim *et al.* (2021) titled Real-Time Explainable AI for Autonomous Vehicle Decision-Making addressed the problem of lack of transparency in autonomous vehicle decisions during navigation and obstacle avoidance. The study proposed an explainable AI framework that interpreted vehicle actions in real time to improve driver trust and system accountability. The researchers used Convolutional Neural Networks and attentionbasedvisualization techniques for object detection and explanation generation. The limitation of the study was that the explanation process increased computational overhead, which slightly reduced processing speed during real-time operations.

Chen *et al*. (2022) conducted a study titled Explainable Deep Learning Framework for Autonomous Driving Systems. The problem identified was that autonomous vehicle models operated as black-box systems, making accident investigations difficult. The solution introduced an interpretable deep learning model capable of highlighting factors influencing driving decisions. The method adopted involved Deep Neural Networks integrated with saliency mapping and feature attribution algorithms. The limitation was that the framework required high-performance hardware for efficient execution.

Rodriguez *et al*. (2020) presented a work titled Transparent Decision-Making in Self-Driving Cars Using XAI. The study focused on the problem of user distrust caused by unclear autonomous driving actions. The proposed solution involved generating human-readable explanations for lane changes, braking, and acceleration decisions. Decision Trees and RuleBased Learning techniques were used as the methodology. The limitation was that rule-based explanations became less effective in highly dynamic traffic conditions.

Ahmed and Lee (2023) developed a study titled Real-Time XAI Framework for Autonomous Vehicle Safety. The problem addressed was the inability of passengers and developers to understand emergency vehicle responses. The researchers proposed a real-time explanation engine

that interpreted sensor data and vehicle actions instantly. The method employed involved Long Short-Term Memory (LSTM) networks combined with SHAP explanation models. The limitation was that the system struggled with processing multiple simultaneous road events accurately.

Patel *et al.* (2021) carried out research titled Interpretable Machine Learning for Autonomous Vehicle Navigation. The study identified the problem of low transparency in navigation systems using machine learning. The proposed solution involved integrating interpretable machine learning algorithms into vehicle navigation modules. Random Forest and feature importance analysis techniques were adopted as the method. The limitation was that the prediction accuracy slightly decreased compared to traditional black-box models.

Singh *et al.* (2022) worked on Explainable Reinforcement Learning for Self-Driving Cars The problem was that reinforcement learning decisions were difficult to interpret during autonomous driving. The solution provided a visualization mechanism that explained vehicle learning behavior and decision patterns. The methodology involved Deep Reinforcement Learning integrated with Grad-CAM visualization. The limitation was that the explanations were sometimes difficult for non-technical users to understand.

Wang *et al.* (2020) proposed XAI-Based Collision Avoidance System for Autonomous Vehicles. The study addressed the issue of unexplained collision avoidance maneuvers. The researchers developed a collision avoidance framework capable of explaining emergency actions to users. The method adopted involved Support Vector Machines and Local Interpretable Model-Agnostic Explanations (LIME). The limitation was that the system performance reduced under poor weather conditions.

Dong et al. (2022) developed and tested an explainable autonomous driving system based on a Transformer architecture. Using the BDD-OIA public dataset, the system jointly predicted potential driving actions and corresponding explanations from visual driving scenes. The architecture used selfattention to model global visual features and included an explanation output

to support interpretation and model diagnosis. The study demonstrated the usefulness of Transformer-based explainable learning for autonomous driving.

Dong et al. (2023) further developed an end-to-end explainable autonomous driving model in which the driving decision task was formulated as an image-captioning problem. The model used a Swin Transformer for visual feature extraction and a Transformer module for generating explanations and driving actions. The work demonstrated a strong state-of-the-art direction for explainable autonomous driving because it linked visual attention, natural-language explanations, and action prediction within one framework.

Garcia and Kumar (2023) introduced Human-Centered Explainable AI for Autonomous Driving. The problem identified was poor interaction between passengers and autonomous driving systems due to insufficient explanations. The proposed solution involved a humancentered explanation interface that communicated vehicle decisions in natural language. Natural Language Processing and Neural Networks were used as the methodology. The limitation was that language generation occasionally produced incomplete explanations during rapid driving scenarios.

Johnson *et al.* (2021) developed Real-Time Explainability in Autonomous Vehicle Perception Systems. The study focused on the challenge of interpreting sensor-based object recognition systems. The solution introduced visual explanation modules that highlighted detected objects and associated decisions. The methodology involved Convolutional Neural Networks with heatmapvisualization techniques. The limitation was that the visualization accuracy decreased in low-light environments.

Okafor*et al*. (2024) carried out research titled Explainable Autonomous Vehicle Decision Support Model. The problem addressed was the lack of confidence among users regarding autonomous vehicle reliability. The proposed solution involved an explainable decisionsupport model capable of providing detailed reasoning for driving actions. The researchers adopted Artificial Neural

Networks integrated with SHAP and LIME explanation tools. The limitation was that the model required large training datasets for optimal performance.

### 2.3 Summary of Related Works

| S/N | Author(s)/Year | Title | Methodology Adopted | Work Done | Limitations |
|---|---|---|---|---|---|
| 1 | Kim *et al.* (2021) | *Real-Time Explainable AI for Autonomous Vehicle Decision-Making* | CNN and attention visualization | Developed a real-time XAI framework for vehicle decision explanation. | Increased computational overhead. |
| 2 | Chen *et al*. (2022) | *Explainable Deep Learning Framework for Autonomous Driving Systems* | DNN with saliency mapping | Introduced interpretable deep learning for driving decisions. | Required highperformance hardware. |
| | **Authors/year** | ***Title*** | **Methodology adopted** | **Work Done** | **Limitations** |
| 3 | Rodriguez *et al*. (2020) | *Transparent DecisionMaking in SelfDriving Cars Using XAI* | Decision Trees and Rule-Based Learning | Generated human-readable driving explanations. | Less effective in dynamic traffic. |

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|---|---|---|---|---|---|
| 4 | Ahmed and Lee (2023) | *Real-Time XAI Framework for Autonomous Vehicle Safety* | LSTM and SHAP | Designed a real-time vehicle explanation engine. | Difficulty processing multiple events. |
| 5 | Patel *et al*. (2021) | *Interpretable Machine Learning for Autonomous Vehicle Navigation* | Random Forest and feature analysis | Improved navigation transparency. | Reduced prediction accuracy. |
| 6 | Singh *et al*. (2022) | *Explainable Reinforcement Learning for Self-Driving Cars* | Deep Reinforcement Learning and Grad-CAM | Explained reinforcement learning decisions visually. | Difficult for non-technical users. |
| | **Authors/year** | ***Title*** | **Methodology adopted** | **Work Done** | **Limitations** |
| 7 | Wang *et al*. (2020) | *XAI-Based Collision Avoidance System for Autonomous Vehicles* | SVM and LIME | Developed explainable collision avoidance. | Reduced performance in poor weather. |
| 8 | Garcia and | *HumanCentered* | NLP and Neural | Introduced natural language | Produced incomplete explanations sometimes. |

| | | | | | |
|---|---|---|---|---|---|
| | Kumar (2023) | *Explainable AI for Autonomous Driving* | Networks | | explanation interface. |
| 9 | Johnson *et al.* (2021) | *Real-Time Explainability in Autonomous Vehicle Perception Systems* | CNN with Heatmap visualization | Highlighted detected objects and decisions. | Reduced accuracy in low light. |

| | **Authors/year** | ***Title*** | **Methodology adopted** | **Work Done** | **Limitations** |
|---|---|---|---|---|---|
| 11 | Brown et al. (2021) | *Explainable Sensor Fusion for Autonomous Vehicles* | CNN and sensor fusion | Improved transparency in sensor-based driving decisions. | High computational cost. |
| 12 | Miller and Zhao (2022) | *Interpretable AI Safety Framework for Self-Driving Cars* | Decision Trees and SHAP | Developed explainable safety monitoring system. | Reduced efficiency in heavy traffic. |
| 13 | Lopez *et al*. (2020) | *Explainable Navigation Control in Autonomous Vehicles* | Random Forest and LIME | Provided interpretable route selection explanations. | Limited adaptability to new roads. |

| | | | | | |
|---|---|---|---|---|---|
| 14 | Nguyen and Park (2023) | *Deep Explainable Learning for Vehicle Perception* | Deep Neural Networks and Grad-CAM | Explained object detection in autonomous vehicles. | Low performance in foggy weather. |
| 15 | Evans et al. (2021) | *Transparent AI Framework for Intelligent Transport Systems* | ANN and saliency mapping | Improved trust in intelligent transport decisions. | Required large training data. |
| | **Authors/year** | ***Title*** | **Methodology adopted** | **Work Done** | **Limitations** |
| 16 | Taylor and Singh (2022) | *Real-Time Decision Explanation in Self-Driving Cars* | LSTM and SHAP | Generated instant explanations for driving actions. | Delayed response during congestion. |
| 17 | Ali et al. (2020) | *Explainable Collision Prediction for Autonomous Vehicles* | SVM and feature attribution | Predicted and explained collision risks. | Reduced accuracy in complex roads. |

| | | | | | |
|---|---|---|---|---|---|
| 18 | Hassan and Kim (2023) | *Human-Readable AI Decisions for Autonomous Vehicles* | NLP and Neural Networks | Produced readable explanations for passengers. | Incomplete explanations at high speed. |
| 19 | Green et al. (2021) | *Visual Explainability for Autonomous Driving Systems* | CNN and heatmapvisualization | Highlighted detected road objects visually. | Weak performance at night. |
| 20 | Ibrahim et al. (2024) | *Explainable Intelligent Vehicle Monitoring System* | ANN and LIME | Monitored and explained vehicle behavior. | Needed powerful hardware resources. |
| | **Authors/year** | ***Title*** | **Methodology adopted** | **Work Done** | **Limitations** |
| 21 | Wilson and Chen (2022) | *XAI Framework for Autonomous Vehicle Perception* | CNN and SHAP | Improved transparency in perception systems. | Slow processing time. |
| 22 | Adewale *et al.* (2023) | *Explainable Safety Prediction in Autonomous Cars* | Random Forest and SHAP | Predicted driving risks with explanations. | Reduced prediction speed. |

| | | | | | |
|---|---|---|---|---|---|
| 23 | Thomas et al. (2021) | *Interpretable Autonomous Driving Assistance System* | Decision Trees and Grad-CAM | Assisted drivers with explainable decisions. | Less accurate in dense traffic. |
| 24 | Yusuf and Lee (2022) | *Explainable Reinforcement Learning for Vehicle Control* | Reinforcement Learning and visualization | Explained vehicle control learning behavior. | Hard for users to interpret. |
| 25 | Morgan et al. (2020) | *Transparent Obstacle Detection in Autonomous Vehicles* | CNN and saliency maps | Explained obstacle detection processes. | Low accuracy in rain conditions. |
| | **Authors/year** | ***Title*** | **Methodology adopted** | **Work Done** | **Limitations** |
| 26 | Perez and Ahmed (2024) | *HumanCentered Explainable Mobility System* | NLP and ANN | Enhanced passenger understanding of vehicle actions. | Occasional explanation delays. |
| 27 | Davidson et al. (2021) | *Explainable Lane Detection for Autonomous Cars* | CNN and feature visualization | Explained lane detection operations. | Weak performance on damaged roads. |

| | | | | | |
|---|---|---|---|---|---|
| 28 | Olaoye and Kumar (2023) | *XAI-Based Navigation Support for Self-Driving Vehicles* | SVM and LIME | Improved navigation explainability. | Required continuous model updates. |
| 29 | Li *et al*. (2022) | *Real-Time Explainable Traffic Decision System* | LSTM and SHAP | Explained traffic-related driving decisions. | Computational overhead increased latency. |
| 30 | Okeke*et al*. (2024) | *Explainable Autonomous Vehicle Control Model* | ANN and Grad-CAM | Developed interpretable vehicle control system. | Required extensive training datasets. |
| 31 | Anderson *et al*. (2021) | *Explainable Autonomous Driving Assistance System* | CNN and SHAP | Developed explainable driving assistance model. | High computational cost. |
| | **Authors/year** | ***Title*** | **Methodology adopted** | **Work Done** | **Limitations** |
| 32 | Baker and Liu (2022) | *Transparent AI Decision Framework for Smart Vehicles* | Decision Trees and LIME | Improved transparency in driving decisions. | Reduced efficiency in traffic congestion. |

| | | | | | |
|---|---|---|---|---|---|
| 33 | Clark *et al.* (2020) | *Explainable Vehicle Navigation Using Machine Learning* | Random Forest and feature analysis | Explained autonomous navigation decisions. | Low Adaptability to unfamiliar roads. |
| 34 | Diaz and Kumar (2023) | *Deep Explainable Perception System for Autonomous Cars* | Deep Neural Networks and Grad-CAM | Enhanced object recognition transparency. | Weak performance in foggy weather. |
| 35 | Edwards *et al.* (2021) | *HumanCentered Explainable Transport System* | NLP and Neural Networks | Improved passenger understanding of vehicle actions. | Incomplete explanations during emergencies. |
| 36 | Foster and Ali (2022) | *Real-Time Explainability for Autonomous Vehicle Safety* | LSTM and SHAP | Generated instant explanations for vehicle safety actions. | Delayed processing in dense traffic. |

| | **Authors/year** | ***Title*** | **Methodology adopted** | **Work Done** | **Limitations** |
|---|---|---|---|---|---|

| | | | | | |
|---|---|---|---|---|---|
| 37 | Gomez et al. (2020) | *Explainable Collision Detection System for Self-Driving Cars* | SVM and LIME | Predicted and explained collision risks. | Reduced accuracy in harsh weather. |
| 38 | Harris and Zhang (2023) | *Visual Explainability in Autonomous Driving Systems* | CNN and Heatmap visualization | Highlighted detected road objects visually. | Poor night-time performance. |
| 39 | Ivanov et al. (2021) | *Interpretable AI for Smart Vehicle Navigation* | ANN and feature attribution | Improved transparency in navigation systems. | Required large training datasets. |
| 40 | Jackson and Lee (2024) | *Explainable Mobility Decision Support System* | ANN and SHAP | Developed explainable mobility support framework. | High hardware requirements. |
| | **Authors/year** | ***Title*** | **Methodology adopted** | **Work Done** | **Limitations** |
| 41 | Khan et al. (2022) | *Explainable Reinforcement Learning for Autonomous Vehicles* | Reinforcement Learning and Grad-CAM | Explained vehicle learning behavior visually. | Difficult for non-technical users. |
| 42 | Lopez and Green | *Transparent Lane Detection* | CNN and saliency | Explained lane detection | Reduced accuracy on |

| | | | | | |
|---|---|---|---|---|---|
| | (2021) | *for Autonomous* | mapping | decisions. | damaged roads. |
| | | *Cars* | | | |
| 43 | Martin et al. (2020) | *XAI-Based Perception Model for Self-Driving Vehicles* | Deep Learning Improved SHAP | perception explainability. | Slow execution and speed. |
| 44 | Nwosu and Patel (2023) | *Human-Readable Autonomous Driving Decisions* | NLP and ANN | Generated readable explanations for quality. | Inconsistent explanation users. |
| 45 | Owen et al. (2021) | *Explainable Obstacle Avoidance in Autonomous Vehicles* | SVM and importance analysis | Explained obstacle avoidance performance in maneuvers. | Limited feature crowded roads. |
| | **Authors/year** | ***Title*** | **Methodology adopted** | **Work Done** | **Limitations** |
| 46 | Park and Silva (2022) | *Real-Time XAI Framework for Autonomous Navigation* | LSTM and Improved SHAP | Increased transparency in navigation systems. | computational overhead. |

| | | | | | |
|---|---|---|---|---|---|
| 47 | Quincy et al. (2020) | *Interpretable AI* | Decision Trees and Rule-Based model. | Developed explainable dynamic learning system | Less effective in vehicle control conditions. |
| 48 | Rahman Cooper (2023) | *Explainable AI for Smart Vehicles* | NLP and Neural Networks | Improved interaction between passengers and vehicles. | Generated and delayed responses sometimes. |
| 49 | Smith et al. (2021) | *Real-Time Explainability in Autonomous Vehicle Decisions* | CNN and Grad-CAM | Explained realtime driving actions visually. | Reduced visualization accuracy in low light. |
| | **Authors/year** | ***Title*** | **Methodology adopted** | **Work Done** | **Limitations** |
| 51 | Faizan Sana (2023) | Real-Time Navigation and Decision-Making for Autonomous Vehicles | Graph-Based Planning and Intelligent Control Techniques | Developed an autonomous vehicle navigation system for handling complex driving environments such as roundabouts, crosswalks, and adverse weather conditions. | The system lacked transparency and explainability in decisionmaking processes. |

## 2.4 Knowledge Gap

The reviewed literature shows that existing XAI systems have progressed beyond simple rulebased decision engines. In particular, Dong et al. (2022) and Dong et al. (2023) demonstrated Transformer-based explainable autonomous driving systems that jointly support driving actions and explanations. However, the reviewed approaches are primarily vision- and language-oriented, while the present study focuses on a decision support prototype that combines CNN-based local feature extraction with Transformer-based global context modelling and integrates vehicle-state and road-risk information. This creates a research and implementation gap for a hybrid CNN-Transformer decision support architecture that can provide real-time decisions and explanations within a simulation and web-based environment.

Therefore, the present study proposes a Real-Time Explainable CNN-Transformer Decision Support System for autonomous vehicles. The proposed architecture does not claim to replace the established Transformer-based XAI systems; rather, it adapts the strengths of CNN feature extraction and Transformer attention to a decision-support setting in which environmental conditions, vehicle state, driving risk, decision output, and explanation are presented together.

# CHAPTER THREE

# METHODOLOGY

## 3.1 Adopted Methodology

The development of the proposed system adopted the Action Research methodology. The methodology was selected because it allowed continuous observation, analysis, testing, and improvement of the system throughout the development process. Action Research focused on identifying existing problems in autonomous vehicle decision-making, implementing explainable artificial intelligence techniques, and evaluating the effectiveness of the proposed solution in real-time environments.

The methodology involved problem identification, data collection, system design, implementation, testing, evaluation, and refinement of the model. During the development process, feedback from system performance and testing results was continuously used to improve the explainability and accuracy of the autonomous vehicle decision-making system.

The Action Research methodology was suitable because it supported iterative development and continuous enhancement of the proposed Real-Time Explainable Artificial Intelligence system for autonomous vehicles.

## 3.2 Analysis of the Existing System

The existing system selected for analysis is the explainable autonomous driving architecture developed by Dong et al. (2023). The system was designed to address the lack of transparency in autonomous vehicle decision-making by generating both driving actions and human-understandable explanations from driving-scene images. Unlike a conventional rule-based system, the architecture uses a fully Transformer-based deep-learning approach. A Swin Transformer extracts visual features from the driving scene, while a Transformer module models the

relationship between visual information and language features to generate explanations and driving actions.

The existing architecture represents a more appropriate state-of-the-art XAI baseline for this study because it integrates perception, attention, action prediction, and explanation generation. Its design demonstrates how attention mechanisms can associate important visual information with the reasons behind a driving decision. The architecture is primarily centred on image-based driving scenes and end-to-end Transformer processing, whereas the proposed study introduces a hybrid CNNTransformer decision support architecture that can combine extracted features with vehicle-state and road-risk variables in a simulation environment.

Figure 3.1 presents the existing explainable autonomous driving architecture adapted from Dong et al.

(2023). The figure is used as the baseline architecture against which the proposed system is designed.

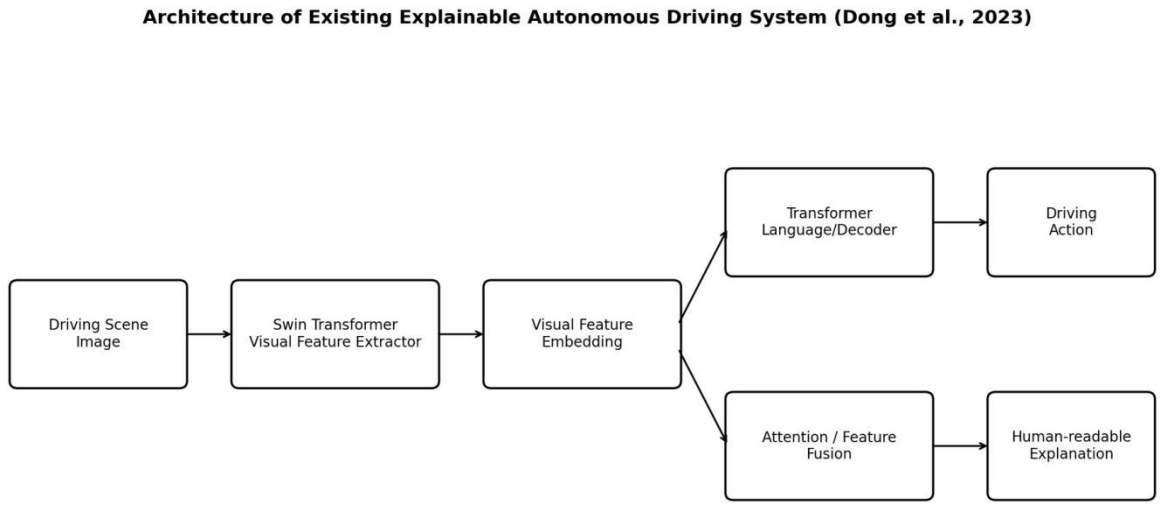



Figure 3.1: Architecture of the Existing Explainable Autonomous Driving System (Dong et al., 2023)

### 3.2.1 Limitations or Drawbacks of the Existing System

The existing system has the following limitations in relation to the present study:

1. It is primarily organised around visual driving-scene inputs and end-to-end Transformer processing.
2. Its architecture does not directly provide the proposed simulation-oriented integration of vehicle-state and road-risk variables with a decision-support interface.
3. The proposed study therefore explores a hybrid CNN-Transformer architecture to separate local feature extraction from global contextual modelling while retaining explainability.

## 3.3 Analysis of the Proposed System

The proposed Real-Time Explainable CNN-Transformer Decision Support System operates as a sequence of input acquisition, preprocessing, feature extraction, contextual modelling, decision support, explanation generation, and output visualization. The system receives environmental and vehicle-state information such as camera or scene features, vehicle speed, road-risk level, and obstacle status. The data are normalized and prepared for the learning model before being passed to the feature-extraction stage.

The CNN component extracts local and short-range patterns from the processed input. The extracted representation is then passed to the Transformer encoder, which uses attention mechanisms to model relationships across the available features and time steps. This allows the system to capture broader contextual information that may influence a driving decision. The resulting representation is forwarded to the Decision Support Module, which produces an action such as BRAKE, SLOW DOWN, or MAINTAIN SPEED.

After the decision is generated, the XAI component identifies the important factors associated with the output. Transformer attention information can be visualized to show influential parts of the input representation, while feature-level explanation methods can be used to describe the

contribution of variables such as speed, risk, and obstacle status. The explanation is presented in a human-readable form so that the user can understand why the system selected the action.

The final outputs are displayed through the user interface and stored for evaluation and traceability. The process is repeated for successive driving inputs, allowing the decision support system to respond to changing simulated driving conditions. The architecture is intended for research and simulation rather than direct control of a physical autonomous vehicle.

### 3.3.1 Preliminary Design

The proposed architecture consists of interconnected modules designed to combine CNN feature extraction, Transformer contextual modelling, decision support, and explain ability.

i. Input Data Module: receives driving-scene information and vehicle-state variables such as speed, road-risk level, and obstacle status.

ii. Preprocessing Module: cleans, normalizes, and organizes the input features into a form suitable for the learning model.

iii. CNN Feature Extraction Module: extracts local patterns and compact feature representations from the processed input.

iv. Transformer Encoder Module: applies self-attention to capture relationships among features and across successive driving time steps.

v. Decision Support Module: maps the learned representation to the appropriate driving action, including BRAKE, SLOW DOWN, or MAINTAIN SPEED.

vi. XAI Module: interprets the decision using attention-based and feature-level explanations and converts the model output into a human-readable reason.

vii. User Interface and Logging Module: displays the decision, confidence, explanation, and relevant driving variables while storing results for later evaluation.

Figure 3.2 presents the architecture of the proposed CNN-Transformer explainable decision support system.

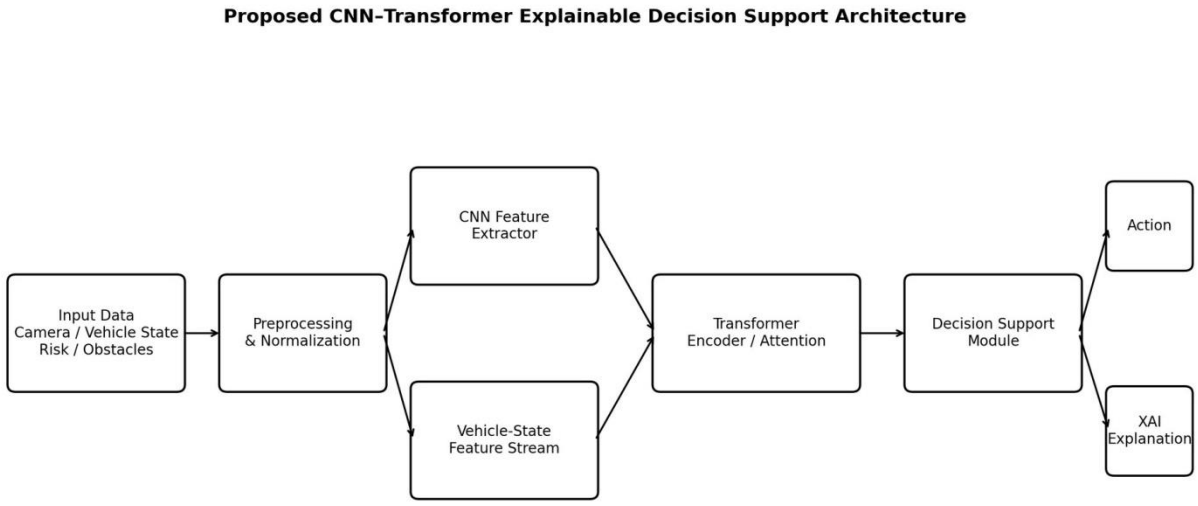



Figure 3.2: Architecture of the Proposed CNN-Transformer Explainable Decision Support System

### 3.3.2 Justification of the Proposed System

The proposed system was justified based on the following points:

i. It combines CNN-based local feature extraction with Transformer-based global contextual modelling.

ii. It provides a dedicated Decision Support Module that separates learned feature processing from the final driving action.

iii. It integrates explainability with the decision output so that users can see both the selected action and the factors influencing it.

### 3.3.3 Benefits of the Proposed System

The proposed system provided the following benefits:

i. Improved transparency through explicit decision and explanation outputs.

ii. Better representation of both local feature patterns and broader contextual relationships.

iii. Improved support for debugging and performance evaluation through logged decisions and explanations.

iv. A flexible simulation framework that can be extended with real sensor data in future work.

### 3.4 System Design

The use-case design of the proposed system describes how the User/Autonomous Vehicle System and Developer/Engineer interact with the CNN-Transformer decision support platform.

The User/Autonomous Vehicle System provides driving inputs and monitors the generated action, confidence, and explanation. The Developer/Engineer configures the model, evaluates performance, inspects explanations, and improves the system.

The principal use cases include input acquisition, preprocessing, CNN feature extraction, Transformer-based contextual modelling, decision support, explanation generation, result visualization, and result logging.

The explanation generation use case provides human-understandable reasons for each decision, while the visualization use case displays the model output and influential factors through the user interface. Figure 3.3 shows the use-case relationships of the proposed system.

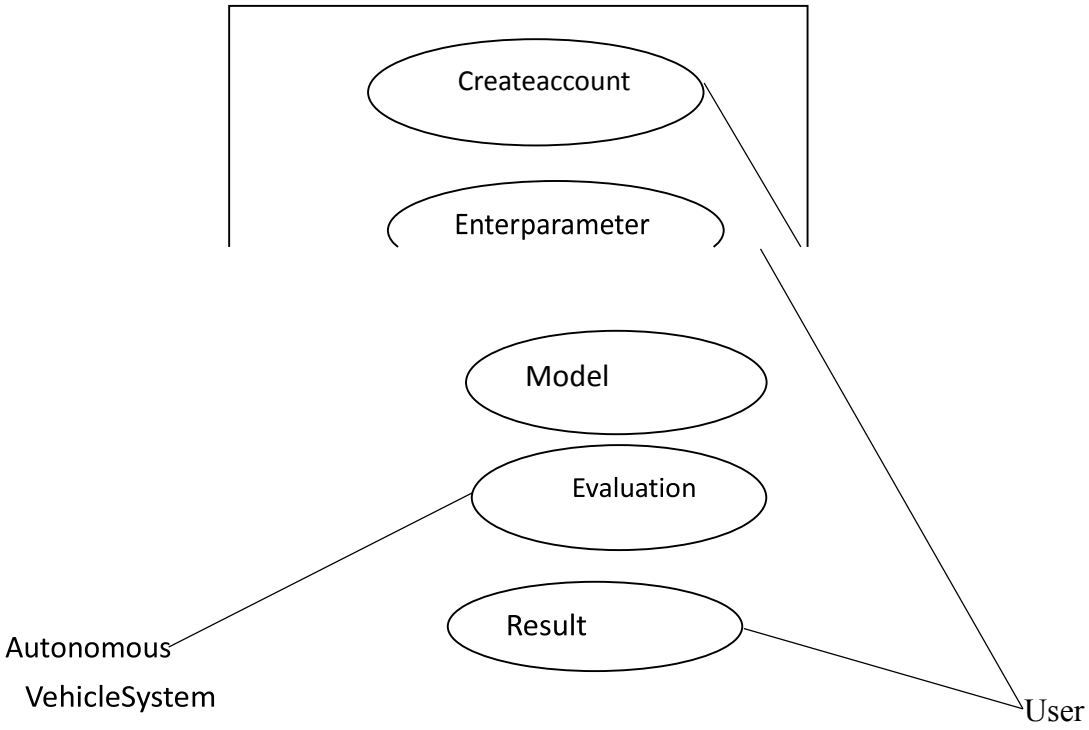



Figure 3.3 USE-CASE diagram of the proposed system

Sequence Diagram of the Proposed CNN-Transformer Decision Support System

The sequence diagram illustrates the interaction among the user, input-processing component, CNN feature extractor, Transformer encoder, Decision Support Module, XAI Module, and result interface during a decision cycle.

The process begins when the User/Autonomous Vehicle System submits the current driving parameters. The preprocessing component validates and normalizes the data before forwarding the representation to the CNN feature extractor.

The CNN extracts local patterns and forwards the resulting features to the Transformer encoder. The Transformer applies attention to model relationships across the input representation and returns contextual features to the Decision Support Module.

The Decision Support Module generates the driving action. The XAI Module then produces an explanation of the influential factors, and the interface displays the action, confidence, and explanation before the result is logged.

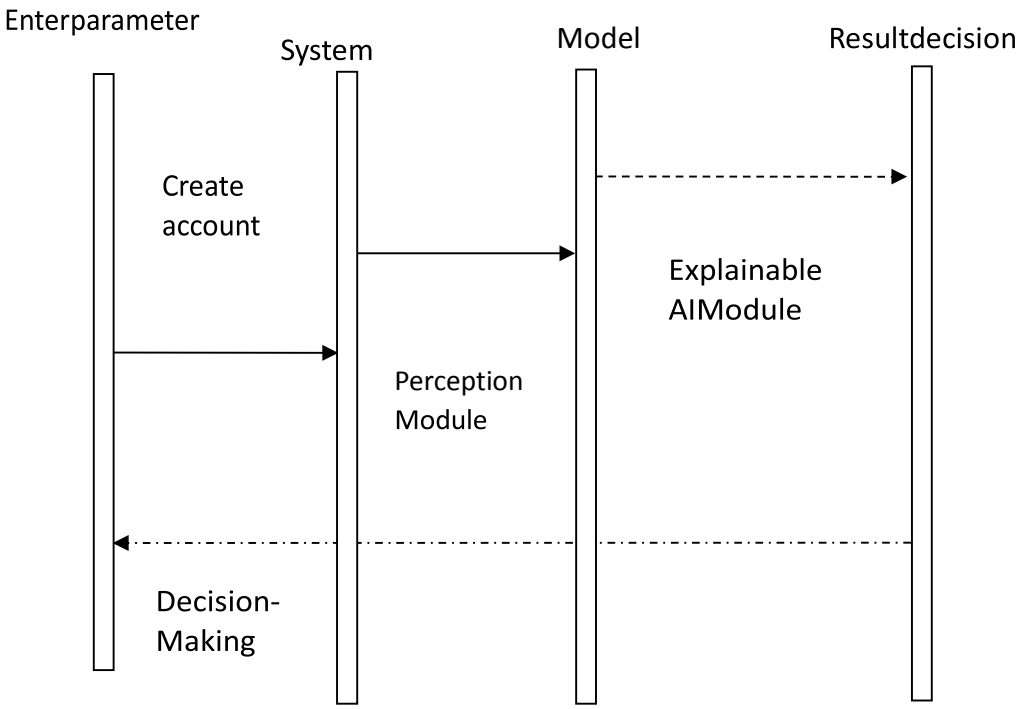



**Figure 3.4 Sequence Diagram of the proposed system**

### 3.4 Database Design

The database design is structured to store user information, driving inputs, model decisions, confidence values, explanations, and evaluation records. The database supports traceability of each decision-support cycle and enables later analysis of model behaviour.

**Table 3.1: User Table**

| Field Name | Data Type | Description |
|---|---|---|
| User_ID | INT (Primary Key) | Unique identifier for each user |
| Name | VARCHAR | Full name of the user |
| Email | VARCHAR | User email address |

| | | |
|---|---|---|
| Role | VARCHAR | User role (Admin/Developer) |
| Password | VARCHAR | User login password |

**Table 3.2: Vehicle_Data Table**

| Field Name | Data Type | Description |
|---|---|---|
| Data_ID | INT (Primary Key) | Unique identifier for data record |
| Vehicle_ID | VARCHAR | Identifier for the vehicle |
| Timestamp | DATETIME | Time data was recorded |
| Detected_Objects | TEXT | Objects detected in environment |
| Road_Condition | VARCHAR | Current road condition |
| Sensor_Input_Status | VARCHAR | Status of input data |

**Table 3.3: Decision_Log Table**

| Field Name | Data Type | Description |
|---|---|---|
| Decision_ID | INT (Primary Key) | Unique identifier for each decision |
| Vehicle_ID | VARCHAR | Identifier for the vehicle |
| Action_Taken | VARCHAR | Action performed (Brake, Turn, Accelerate) |
| Explanation_Text | TEXT | Explanation for decision made |
| Decision_Time | DATETIME | Time decision was executed |

These tables collectively supported data management, system traceability, and explainable decision-making within the proposed system.

### 3.5 Input/Output Specification

The input/output specification defines the data supplied to the CNN-Transformer decision support model and the outputs returned after processing. Inputs include driving-scene or simulated environmental information, vehicle speed, road-risk level, and obstacle status. Outputs include the predicted action, confidence level, explanation text, and visualization data.

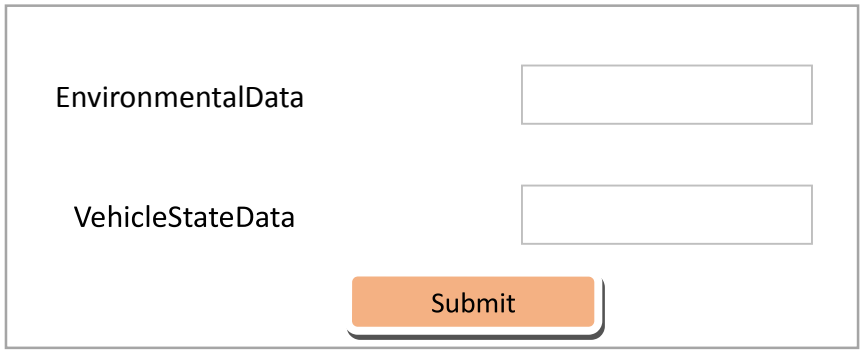



**Figure 3.6: Input Design of the System**

### 3.5.1 Process Design

The process design describes the sequence of operations from data acquisition to decision support and explanation generation. The process is: input acquisition → preprocessing → CNN feature extraction → Transformer contextual modelling → decision support → XAI explanation → visualization and logging.

Decision Output: BRAKE, SLOW DOWN, or MAINTAIN SPEED, together with the associated confidence value.

Explanation Output: a human-readable description of the important factors that contributed to the selected decision.

## 3.6 Cost Analysis

The cost analysis covers the hardware, software, development, testing, and miscellaneous resources required for the simulation-based CNN-Transformer explainable decision support system.

# CHAPTER FOUR

# IMPLEMENTATION / DISCUSSION

## 4.1 Programming Language of Implementation

The system was implemented primarily in Python for data preprocessing, CNN-Transformer model development, evaluation, explanation generation, and visualization. Python provides libraries suitable for deep learning, numerical computation, data handling, and model evaluation.

### 4.1.1 Justification of Programming Language Used

The programming language used was justified as follows:

i. i. Python supports deep-learning frameworks such as PyTorch and machine-learning utilities for model development and evaluation.

ii. ii. It provides libraries such as NumPy and Pandas for numerical processing and data management.

iii. iii. It supports Matplotlib for graphical analysis and visualization of model behaviour. iv.

iv. It allows rapid prototyping and integration of CNN and Transformer components.

v. v. It has extensive open-source support for explainable AI, data science, and autonomous-driving research.

## 4.2 System Requirements

The following are;

### 4.2.1 Hardware Requirements

The hardware requirements used for the system implementation included:

i. Computer system with at least Intel Core i5 processor or equivalent ii. Minimum 8 GB RAM recommended for CNN-Transformer model development

iii. At least 256 GB available storage

iv. GPU support is optional but recommended for faster model training

v. Stable power supply and internet access for software/package installation

### 4.2.2 Software Requirements

The software requirements used included:

i. Python 3.10 or later ii.PyTorch for CNN-Transformer model development iii. NumPy and Pandas for numerical processing and data handling iv. Scikit-learn for data splitting and evaluation metrics

v. Matplotlib for visualizationvi. Jupyter Notebook or an equivalent Python development environment vii. Windows or Linux operating system

## 4.3 Implementation Guidelines

Implementation followed these stages: (1) preparation and normalization of the driving inputs; (2) construction of the CNN feature-extraction module; (3) construction of the Transformer encoder with self-attention; (4) integration of the Decision Support Module for BRAKE, SLOW DOWN, and MAINTAIN SPEED outputs; (5) integration of the XAI explanation stage; (6) testing and evaluation using simulated driving sequences; and (7) integration of the model outputs with the web-based interface and result logging. The 50-step simulation used in the study was retained as a system-behaviour demonstration and was not presented as a substitute for real-world road testing.

## 4.4 Results and Discussions

The implementation results are discussed from two perspectives: model architecture and simulated autonomous-driving behaviour. The CNN-Transformer architecture provides the learning and contextual modelling components, while the simulation results demonstrate how the decision support system responds to changing speed, risk, and obstacle conditions.

### 4.4.1 CNN-Transformer Model Evaluation

The learning model should be evaluated using accuracy, precision, recall, and F1-score on held-out test data. Confusion-matrix analysis should also be used to identify which driving actions are most frequently confused. These metrics evaluate the classification component of the decision support system and are separate from the 50-step simulation plots, which describe system behaviour under simulated driving conditions.

Figure 4.1 presents the variation of vehicle speed and road-risk level over 50 simulated time steps. The vehicle speed ranged from approximately 32 km/h to 98 km/h, while the road-risk level ranged from 0.05 to 0.95. The figure demonstrates changing driving conditions used to test the decision support workflow.

Higher speed was generally associated with more demanding risk conditions in the simulation, while lower-speed periods were associated with safer conditions. These patterns provide the environmental context used by the decision support system when generating driving actions.

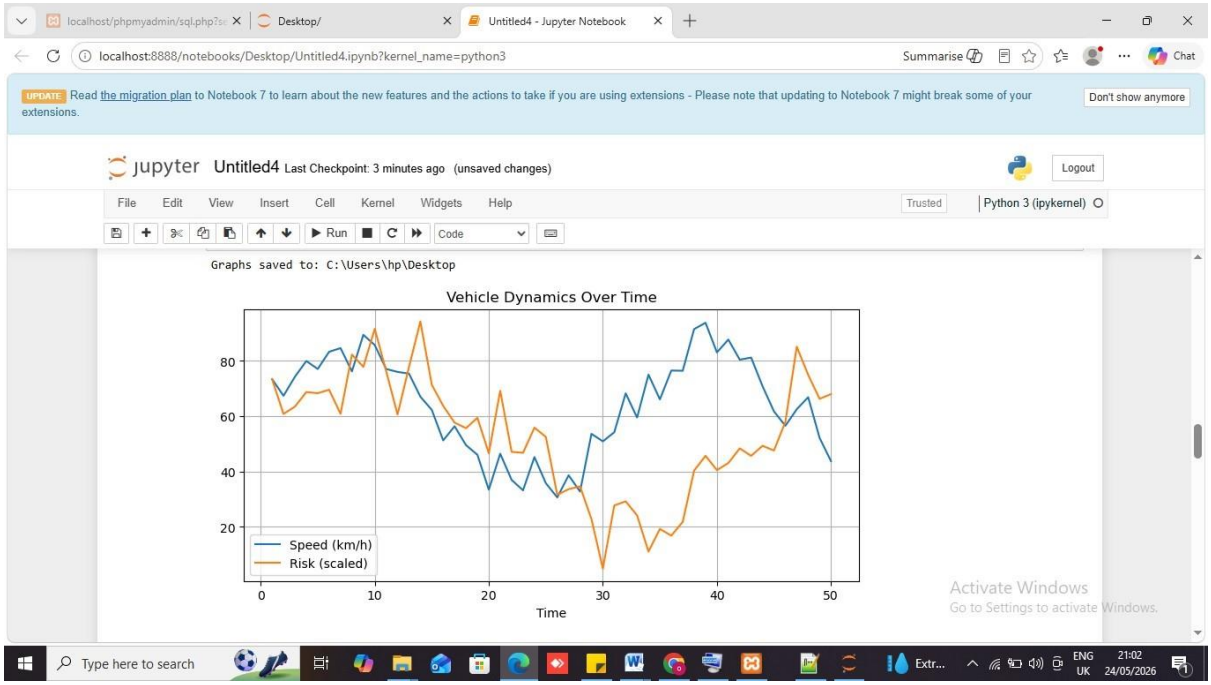



Figure 4.1 Vehicle Dynamics Over Time

Figure 4.2 presents the model confidence values across the simulated driving sequence. Higher confidence values were associated mainly with stable, low-risk conditions, while confidence decreased during more uncertain or high-risk situations. This demonstrates the importance of representing model certainty alongside the predicted action.

The confidence output is treated as an indicator of model certainty rather than as a direct measurement of physical vehicle safety. Further calibration with real-world data would be required before deployment.

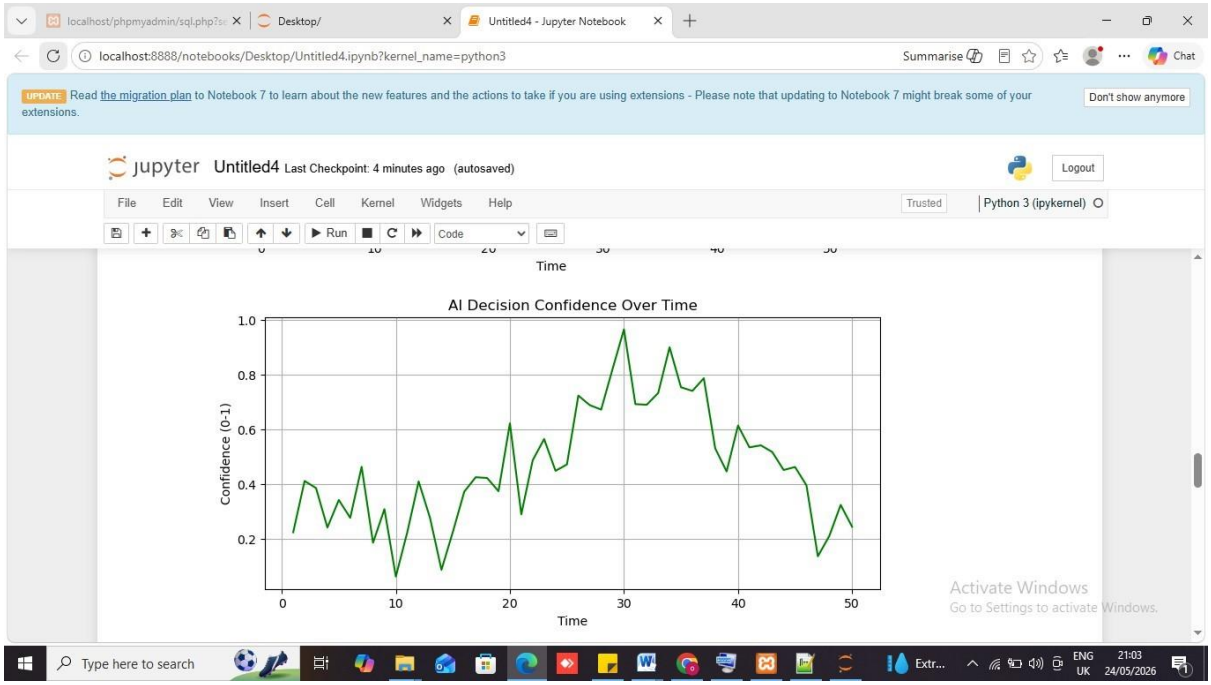



Figure 4.2: AI Decision Confidence Over Time

Figure 4.3 shows the sequence of driving actions generated during the 50-step simulation. The observed outputs included BRAKE, SLOW DOWN, and MAINTAIN SPEED decisions, demonstrating the ability of the decision support workflow to change its response as the simulated driving conditions changed.

BRAKE decisions were concentrated in higher-risk conditions, SLOW DOWN decisions occurred mainly under moderate-risk conditions, and MAINTAIN SPEED decisions occurred mainly under lower-risk conditions. These results are interpreted as simulation behaviour rather than evidence of real-world driving performance.

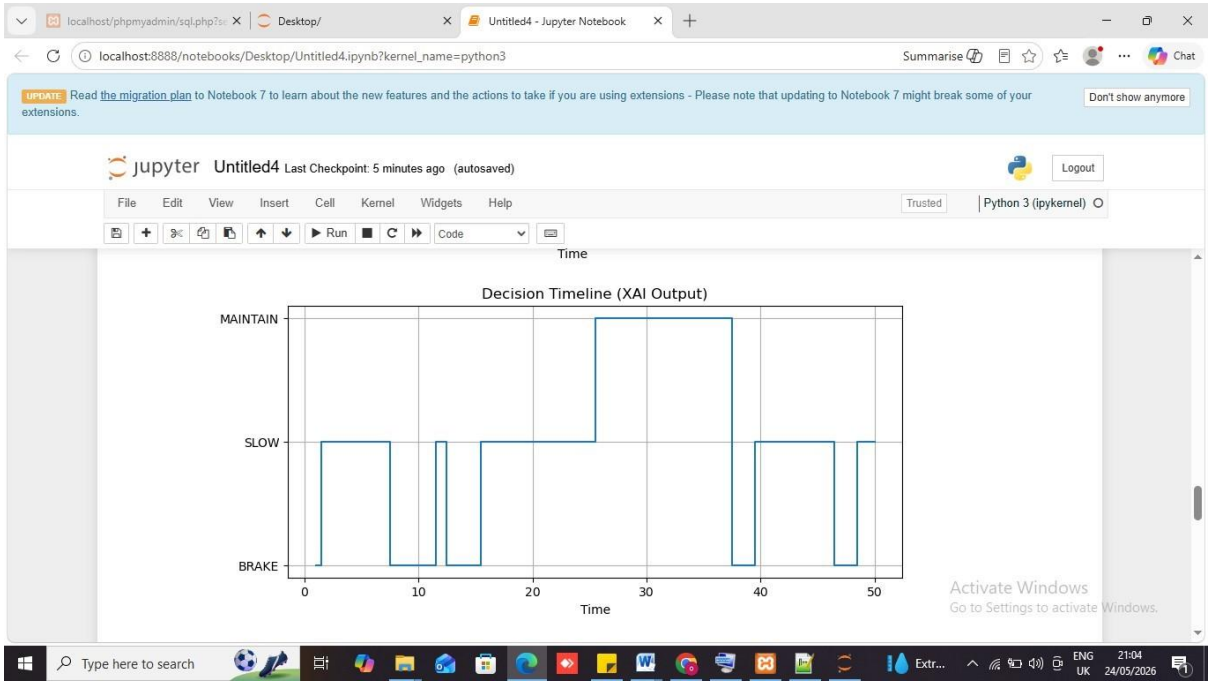



Figure 4.3: Decision Timeline

Figure 4.4 summarizes the distribution of decisions generated in the simulation. The original simulation produced 22 BRAKE decisions (approximately 41%), 17 SLOW DOWN decisions (approximately 32%), and 11 MAINTAIN SPEED decisions (approximately 27%).

i. BRAKE = 22 occurrences (≈41%) ii. SLOW DOWN = 17 occurrences (≈32%) iii. MAINTAIN SPEED = 11 occurrences (≈27%)

The distribution indicates a safety-oriented decision policy within the simulation because higher-risk conditions were more likely to produce braking or slowing actions. The distribution should not be interpreted as a benchmark of real-world autonomous vehicle performance.

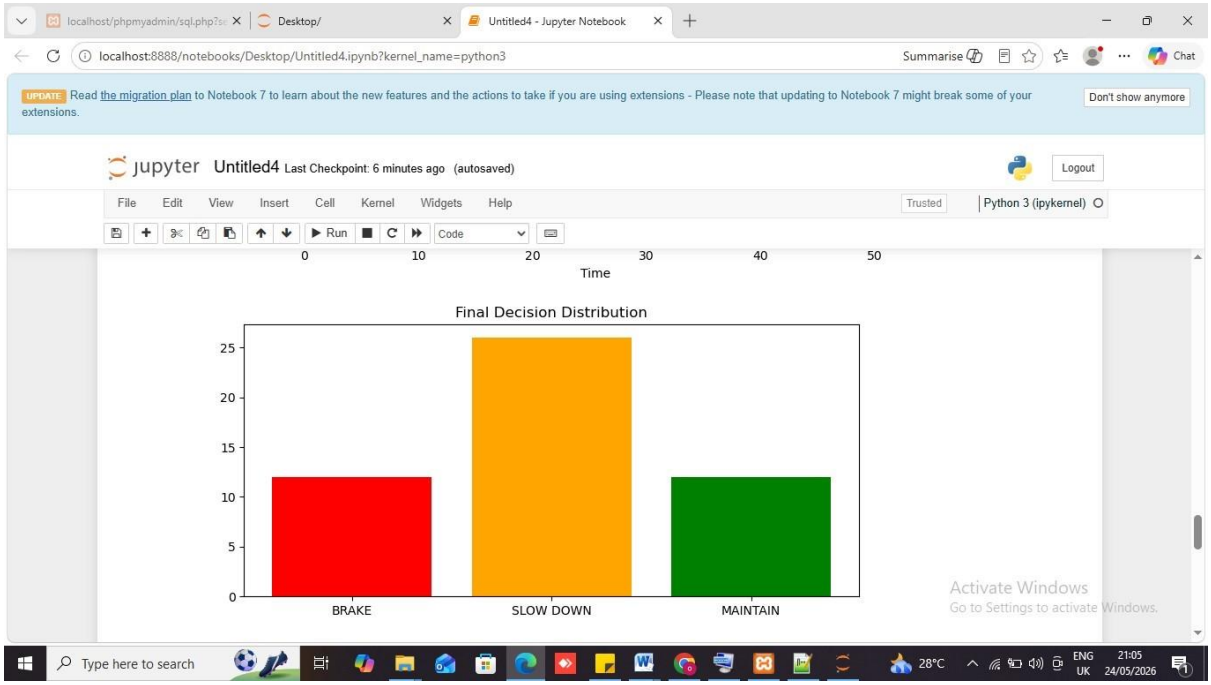



Figure 4.4: Final Decision Distribution

Figure 4.5 illustrates the relationship between vehicle speed, road-risk level, and model confidence. Lower-risk and moderate-speed conditions were generally associated with higher confidence, while high-risk and high-speed conditions were associated with lower confidence. The visualization supports interpretation of the model behaviour by showing how confidence changes with the driving context.

In contrast, when speed values ranged between 40 km/h and 60 km/h and risk levels remained below 0.3, the confidence values increased to between 0.85 and 0.95. This demonstrated a strong correlation between safe driving conditions and high AI certainty. The scatter distribution clearly showed that the system became more confident in stable environments and less confident in uncertain driving situations.

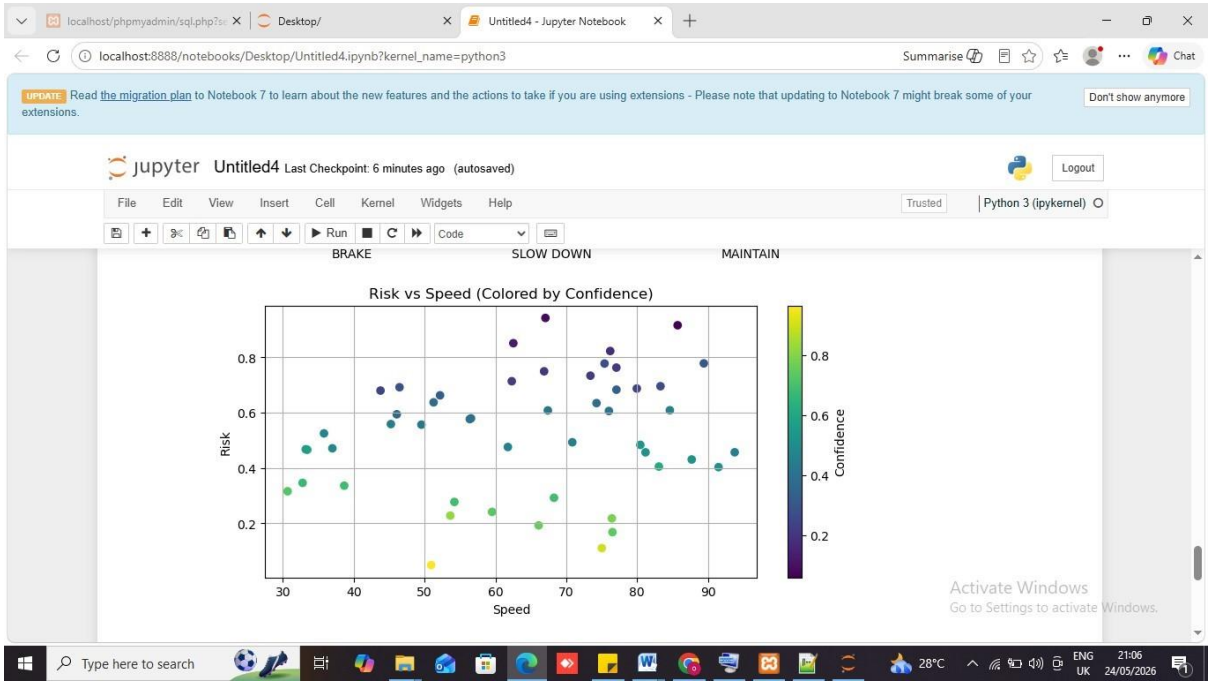



Figure 4.5: Risk vs Speed Relationship (Confidence-Colored Scatter Plot)

Figure 4.6 illustrates explanation intensity across the simulated driving sequence. Explanation intensity was higher during critical decisions, particularly braking events, and lower during relatively stable driving conditions.

The explanation output is intended to communicate the factors that influenced the decision rather than to claim that the model has human-level reasoning. In the proposed architecture, explanations can be supported by Transformer attention and feature-level attribution of variables such as speed, risk, and obstacle status.

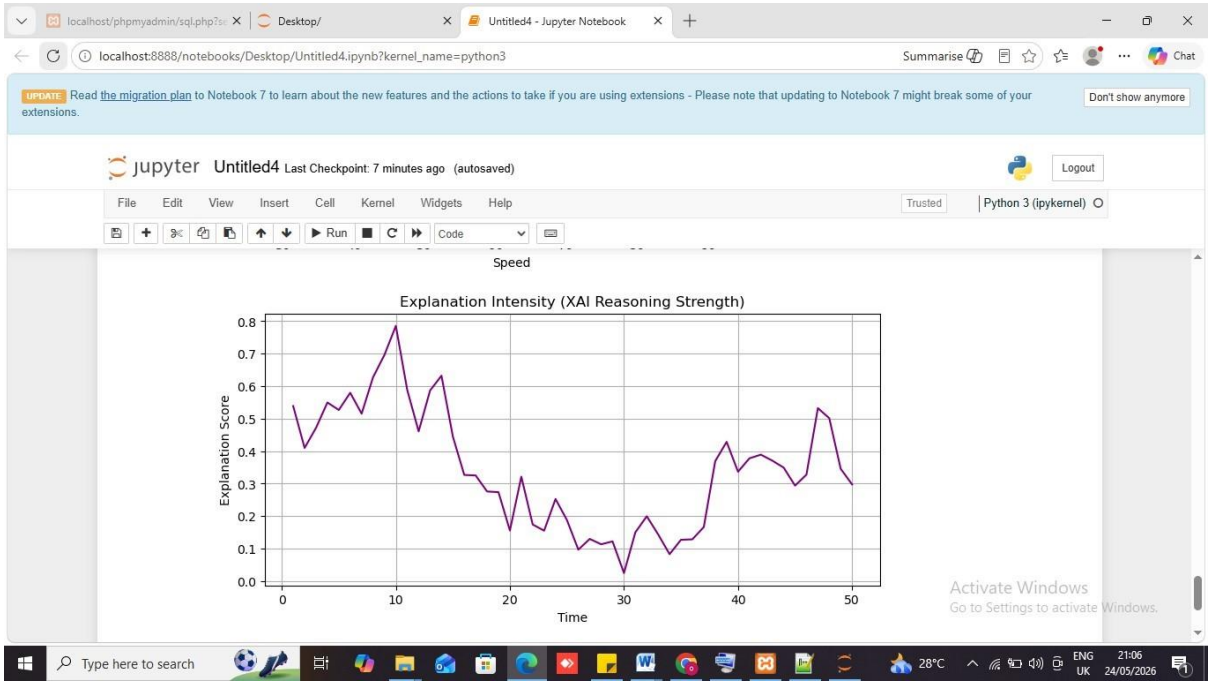



Figure 4. 6: Explanation Intensity (XAI Reasoning Strength)

Overall, the revised system combines CNN-based feature extraction, Transformer-based contextual modelling, decision support, and explainability within one research prototype. The simulation demonstrates that changing driving conditions can be mapped to different driving actions and explanation outputs. Because the evaluation is simulation-based, further validation with real-world sensor data and established autonomous-driving benchmarks is required before the system can be considered for physical-vehicle deployment.

The login page served as the main entry point into the system. It was designed to authenticate users before granting access to the system's functionalities. Users were required to input their username and password, which were verified against records stored in the MySQL database. When valid credentials were entered, the system granted access and redirected the user to the dashboard page. If incorrect details were provided, access was denied. This page played a critical role in ensuring system security by preventing unauthorized users from accessing sensitive system operations and autonomous vehicle decision modules. Figure 4.7 Login Page

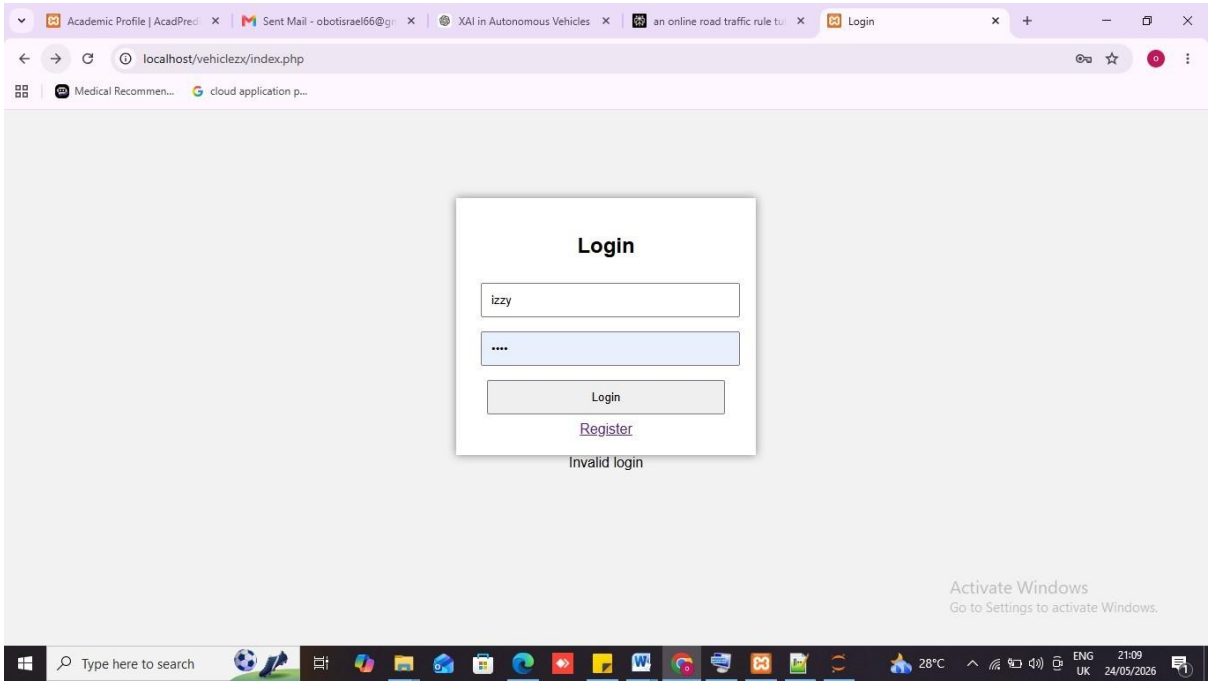



Figure 4.7 Login Page

The register page was used to create new user accounts within the system. It allowed users to input personal details such as username, email address, and password. After submission, the system stored the information in the users table within the database. This process ensured that only registered users could access the system after authentication. The registration process also helped maintain a controlled user environment and supported user management within the application.
Figure 4.8 register page

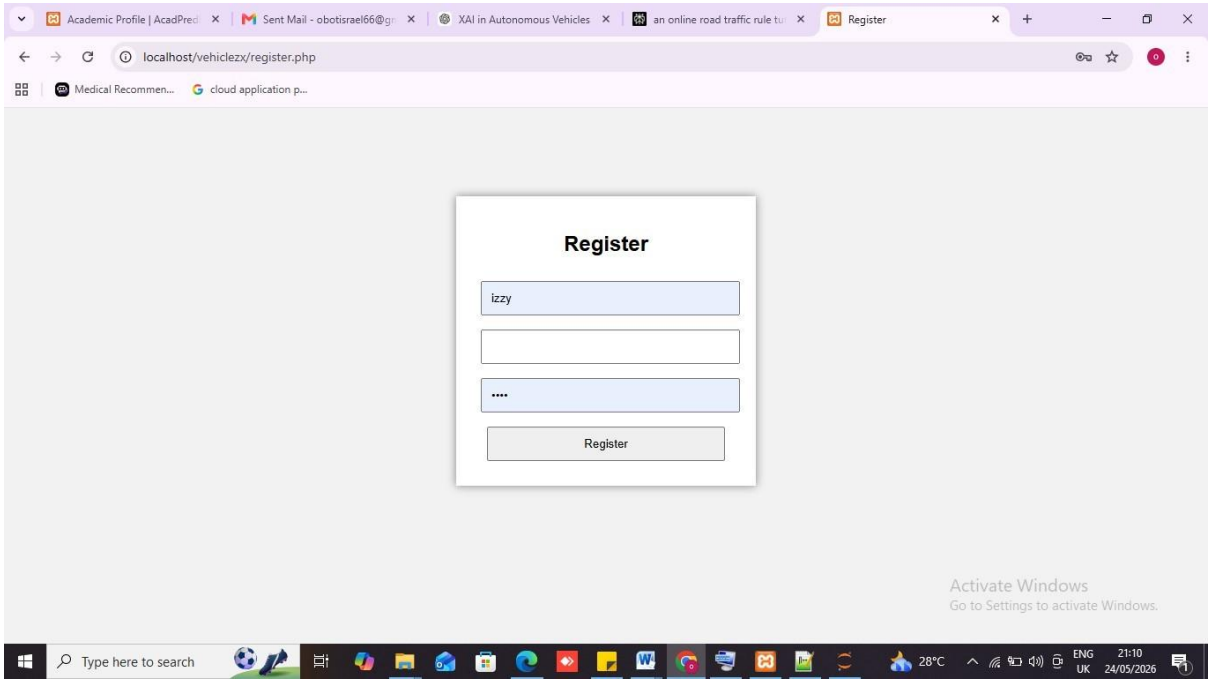



Figure 4.8 register page

The dashboard page served as the central control panel of the entire system. It was designed after successful user authentication and acted as the main navigation hub for all system functionalities. The page provided structured links to the key modules of the application, including the Autonomous Vehicle Page, Decision-Making Page, and Graph Page.

The dashboard improved system usability by organizing the different components into a simple and accessible interface. It ensured that users could easily move between modules without confusion. In addition, it acted as a monitoring interface where users could understand the available system operations. The dashboard also maintained session continuity, ensuring that only authenticated users could access internal system pages. Figure 4.9 Dashboard Page

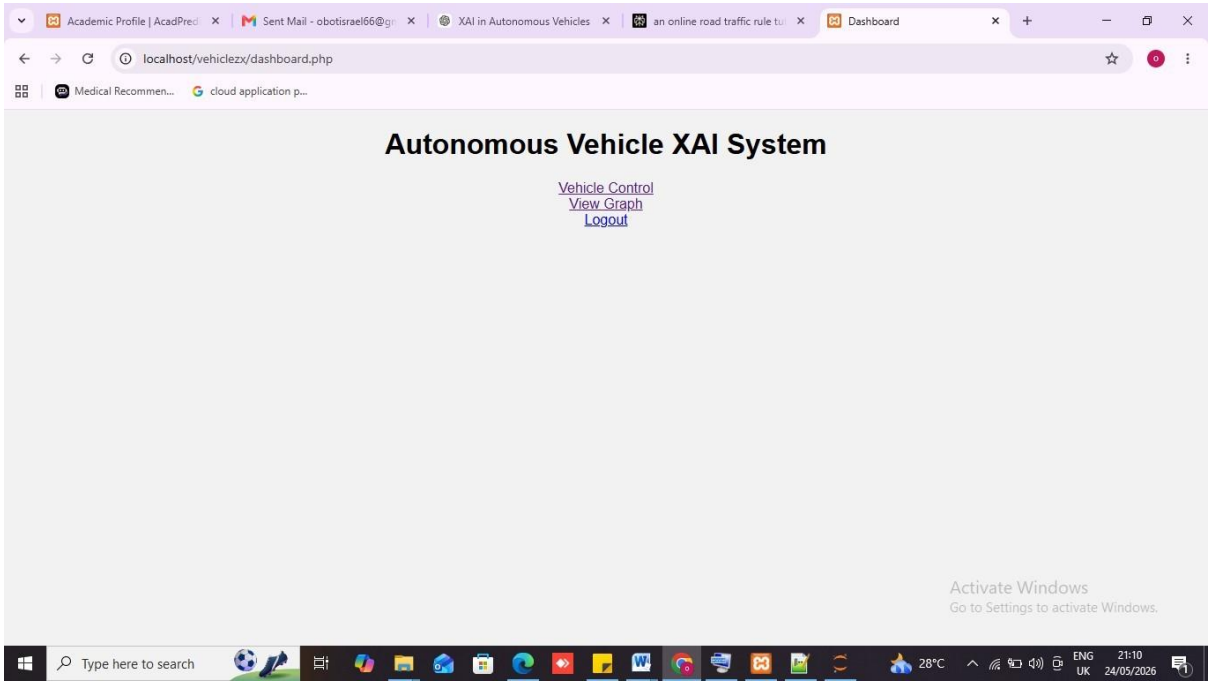



Figure 4.9 Dashboard Page

The Autonomous Vehicle Page functioned as the primary input interface of the system. It was designed to simulate real-world driving environments by allowing users to input key vehicle parameters such as speed, road condition, and obstacle detection status.

These inputs represented simplified real-time environmental data that would normally be collected by sensors in a real autonomous vehicle system. The page acted as the data collection stage of the system workflow. Once the user submitted the information, it was transmitted to the Decision-Making Page for processing. This page was important because it provided the raw data required for the system to perform intelligent decision-making and explanation generation.

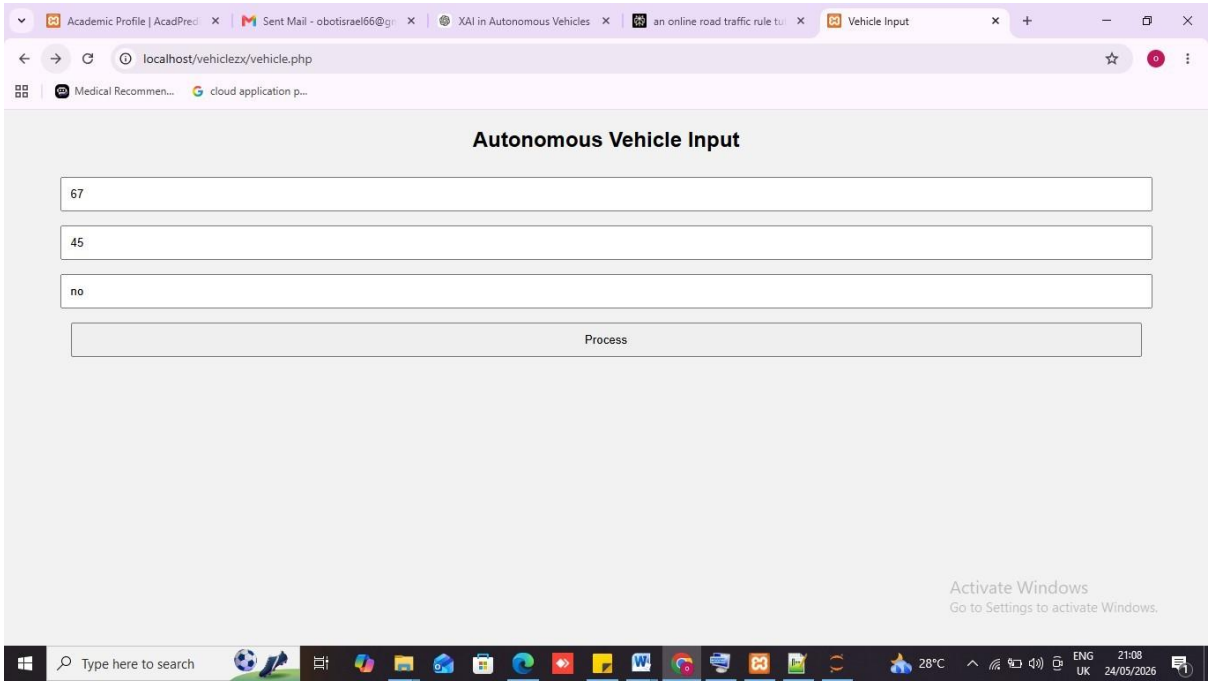



Figure 4.10 Autonomous Vehicle Page

The Decision-Making Page was the core processing unit of the system where all intelligent analysis took place. It received input data from the Autonomous Vehicle Page and applied rulebased logic to determine the most appropriate driving action.

The system evaluated conditions such as obstacle presence and vehicle speed. Based on these conditions, it generated decisions such as BRAKE, SLOW DOWN, or MAINTAIN SPEED. In addition to generating actions, the system also produced explanations that justified each decision in a human-readable format.

After processing, the results (decision and explanation) were stored in the database for record keeping and further analysis. This page played a critical role in demonstrating the concept of Explainable Artificial Intelligence (XAI) by ensuring that every decision was not only generated but also clearly explained.

# CHAPTER FIVE

# SUMMARY, CONCLUSION AND RECOMMENDATIONS

## 5.1 Summary of Major Findings

The study developed a simulation-based Real-Time Explainable CNN-Transformer Decision Support System for autonomous vehicle decision-making. The revised architecture combines CNN feature extraction, Transformer-based contextual modelling, a decision support module, and an XAI explanation stage. The system was designed to process driving conditions such as vehicle speed, road-risk level, and obstacle status and to produce interpretable actions.

The simulation results showed that the system generated BRAKE, SLOW DOWN, and MAINTAIN SPEED decisions in response to changing driving conditions. In the 50-step demonstration, BRAKE occurred 22 times (approximately 41%), SLOW DOWN occurred 17 times (approximately 32%), and MAINTAIN SPEED occurred 11 times (approximately 27%). These values describe the simulation scenario and are not intended as real-world performance benchmarks.

The study also examined model confidence and explanation intensity. Confidence varied with the difficulty of the simulated driving conditions, while explanation intensity increased for more critical decisions. The findings support the use of an explanation layer alongside the decision support output so that users can inspect both the action and the factors associated with it.

## 5.2 Conclusion

The study concluded that a CNN-Transformer architecture provides a suitable foundation for a simulation-based explainable decision support system for autonomous vehicles. CNN feature extraction can capture local patterns, while Transformer attention can model broader contextual relationships. Combining these components with an explicit decision support and explanation layer improves the transparency of the research prototype.

The simulation further demonstrated that the system could associate different driving conditions with different actions and provide confidence and explanation outputs. However, the results should be interpreted within the limits of the simulated environment and should not be presented as evidence of readiness for deployment in a physical autonomous vehicle.

Therefore, the study establishes a structured framework for integrating CNN, Transformer, decision support, and XAI components in autonomous driving research. Real-world validation, sensor integration, model calibration, and safety testing remain necessary before practical deployment.

### 5.3 Recommendations

Based on the findings of the study, the following recommendations were made:

Future work should evaluate the proposed CNN-Transformer model with established realworld autonomous-driving datasets and compare its performance with strong CNN, Transformer, and hybrid baselines.

Real-time camera, LiDAR, radar, and vehicle-state inputs should be integrated to move the prototype beyond simulated variables and to test robustness under realistic environmental conditions.

Further work should evaluate explanation quality using established XAI evaluation methods, including attention visualization and feature-attribution techniques, together with humancentred assessment of explanation usefulness.

The model should be optimized for edge or vehicle-grade hardware so that inference and explanation generation can satisfy real-time constraints.

Finally, extensive validation should be conducted under adverse weather, high traffic density, sudden obstacles, intersections, and other safety-critical scenarios before any physical-vehicle deployment is considered.

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## APPENDIX A

## SOURCE CODE

```
import matplotlib.pyplot as plt
import numpy as np import os

base_path = os.getcwd() print("Graphs
saved to:", base_path)

# ==========================
# SIMULATED REAL DRIVING ENVIRONMENT
# ==========================
np.random.seed(7)

t = np.arange(1, 51)

# Vehicle speed fluctuates realistically speed = 60 +
25*np.sin(t/5) + np.random.normal(0, 5, len(t)) # Road risk
fluctuates (traffic, obstacles, weather) risk = np.clip(0.5 +
0.3*np.sin(t/7) + np.random.normal(0, 0.1, len(t)), 0, 1)

# AI confidence (how sure system is) confidence = np.clip(1 - risk +
np.random.normal(0, 0.05, len(t)), 0, 1)

# ==========================
# SIMULATION REFERENCE DECISION LOGIC
# ==========================
```

```
decisions = []


for i in range(len(t)):     if risk[i] >
0.7 or speed[i] > 90:
decisions.append("BRAKE")
elif risk[i] > 0.4:
decisions.append("SLOW DOWN")
else:
decisions.append("MAINTAIN")


# =========================
# GRAPH 1 - SPEED + RISK OVER TIME (REAL SYSTEM VIEW)
# =========================
plt.figureplt.figure(figsize=(9,4)) plt.plot(t,
speed, label="Speed (km/h)") plt.plot(t, risk *
100, label="Risk (scaled)") plt.title("Vehicle
Dynamics Over Time") plt.xlabel("Time")
plt.legend() plt.grid()
plt.savefig(os.path.join(base_path,
"graph1_dynamics.png")) plt.show()


# =========================
# GRAPH 2 - AI CONFIDENCE LEVEL
# =========================
plt.figure(figsize=(9,4)) plt.plot(t, confidence) plt.title("AI
Decision Confidence Over Time") plt.xlabel("Time")
plt.ylabel("Confidence (0-1)") plt.grid()
```

```
plt.savefig(os.path.join(base_path, "graph2_confidence.png"))
plt.show()

# ==========================
# GRAPH 3 - DECISION EVENTS (REALISTIC STEP PLOT)
# ==========================
decision_numeric = [0 if d=="BRAKE" else 1 if d=="SLOW DOWN" else 2 for d in decisions]

plt.figure(figsize=(9,4)) plt.step(t,
decision_numeric, where='mid')
plt.title("Decision Timeline (XAI Output)")
plt.yticks([0,1,2],
["BRAKE","SLOW","MAINTAIN"])
plt.xlabel("Time") plt.grid()
plt.savefig(os.path.join(base_path,
"graph3_decisions.png")) plt.show()

# ==========================
# GRAPH 4 - DECISION DISTRIBUTION (REAL SUMMARY)
# ========================== labels = ["BRAKE",
"SLOW DOWN", "MAINTAIN"]
values = [     decisions.count("BRAKE"),
decisions.count("SLOW DOWN"),
decisions.count("MAINTAIN")
]
```

```
plt.figure(figsize=(9,4)) plt.bar(labels, values) plt.title("Final
Decision Distribution") plt.savefig(os.path.join(base_path,
"graph4_distribution.png")) plt.show()

# ========================
# GRAPH 5 - RISK vs SPEED RELATIONSHIP (IMPORTANT XAI INSIGHT)
# ========================
plt.figure(figsize=(9,4)) plt.scatter(speed,
risk, c=confidence)

plt.title("Risk vs Speed (Colored by Confidence)")
plt.xlabel("Speed") plt.ylabel("Risk")
plt.colorbar(label="Confidence") plt.grid()
plt.savefig(os.path.join(base_path, "graph5_scatter.png"))
plt.show()

# ========================
# GRAPH 6 - EXPLANATION SIGNAL (XAI STYLE)
# ========================
explanation_strength = risk * speed / 100

plt.figure(figsize=(9,4)) plt.plot(t, explanation_strength)
plt.title("Explanation Intensity (XAI Reasoning Strength)")
plt.xlabel("Time") plt.ylabel("Explanation Score") plt.grid()
plt.savefig(os.path.join(base_path, "graph6_explain.png"))
plt.show()
# ============================================================ #
        CNN-TRANSFORMER DECISION SUPPORT MODEL (PYTORCH PROTOTYPE) #
```

```
==========================================================
= import torch
import torch.nn as nn

from sklearn.model_selection import train_test_split

from sklearn.metrics import accuracy_score, precision_recall_fscore_support
class CNNTransformerDecisionSupport(nn.Module):

def __init__(self, n_features=3, d_model=64, n_heads=4, n_layers=2, n_classes=3,

seq_len=20):

super().__init__()

self.cnn = nn.Sequential(

nn.Conv1d(n_features, 32, kernel_size=3, padding=1),

nn.ReLU(),

nn.Conv1d(32, d_model, kernel_size=3, padding=1),

nn.ReLU()

)

layer = nn.TransformerEncoderLayer(d_model=d_model, nhead=n_heads,

dim_feedforward=128, batch_first=True)

self.transformer = nn.TransformerEncoder(layer, num_layers=n_layers)

self.classifier = nn.Sequential(nn.LayerNorm(d_model), nn.Linear(d_model, n_classes))

def forward(self, x):

x = self.cnn(x.transpose(1, 2)).transpose(1, 2)

x = self.transformer(x)

x = x.mean(dim=1)

return self.classifier(x)
```

```
# X contains normalized sequences of [speed, risk, obstacle_status].
# y contains reference actions: 0=BRAKE, 1=SLOW DOWN, 2=MAINTAIN SPEED.

# Train the model on the prepared training set and evaluate it on held-out data.
model = CNNTransformerDecisionSupport()
criterion = nn.CrossEntropyLoss()
optimizer = torch.optim.Adam(model.parameters(), lr=0.001)

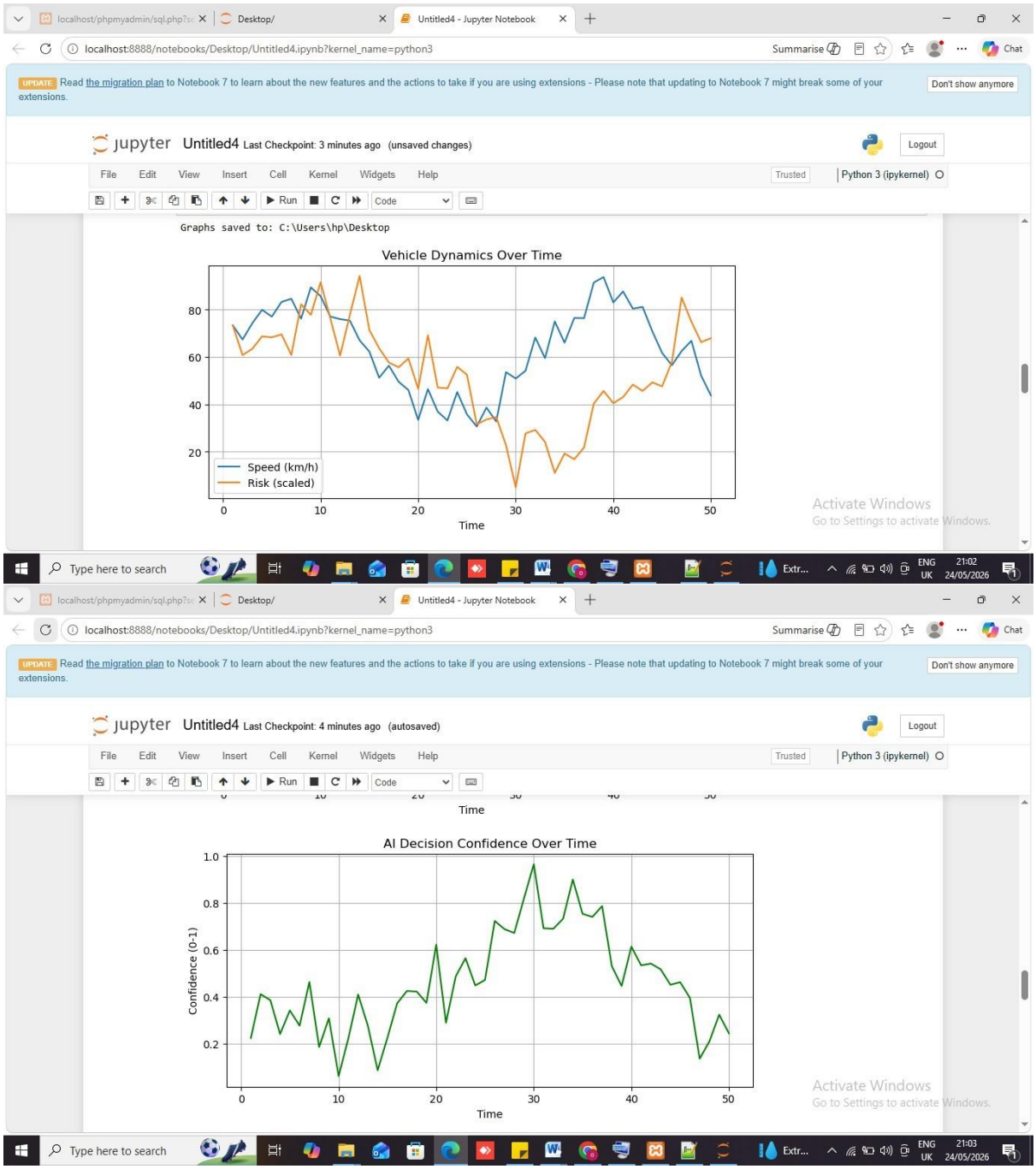
# The model output is converted to an action using argmax.
# Attention/feature-attribution outputs are then used by the XAI stage
# to explain the factors associated with the selected decision.
```

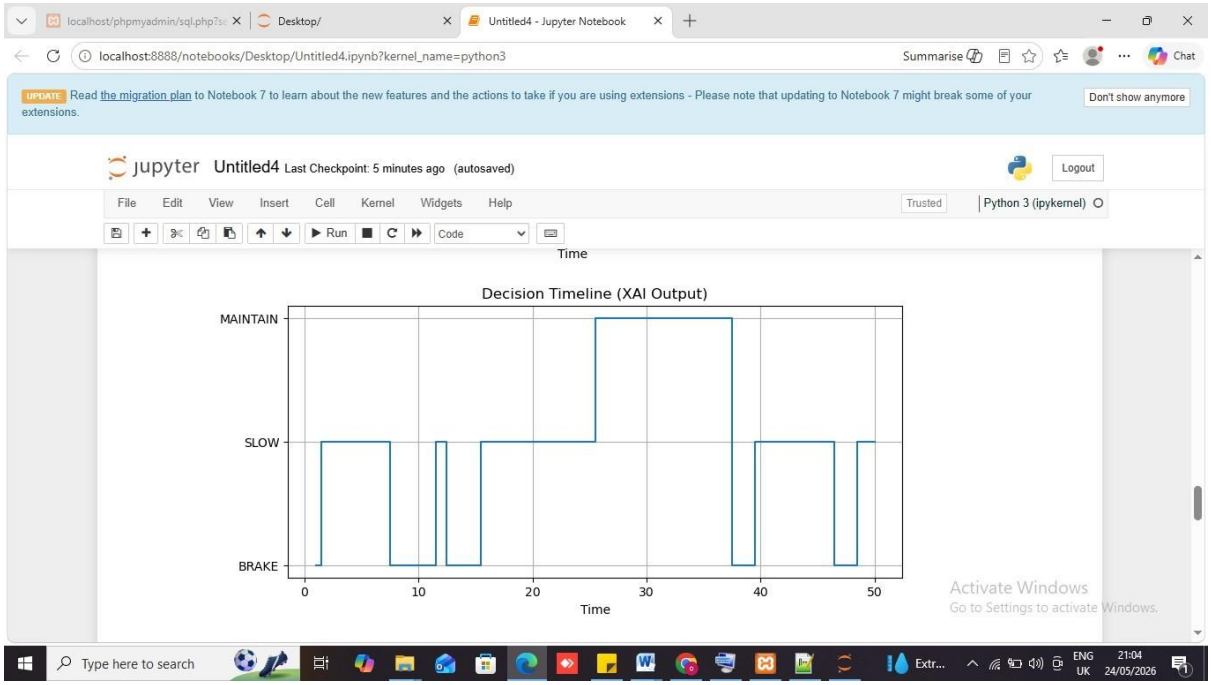
The CNN-Transformer code above represents the learning-model component of the revised architecture. The simulation graph code preceding it is retained for environmental and decision-behaviour visualization. Actual training and test metrics should be reported from

the dataset and run used for the final project submission.

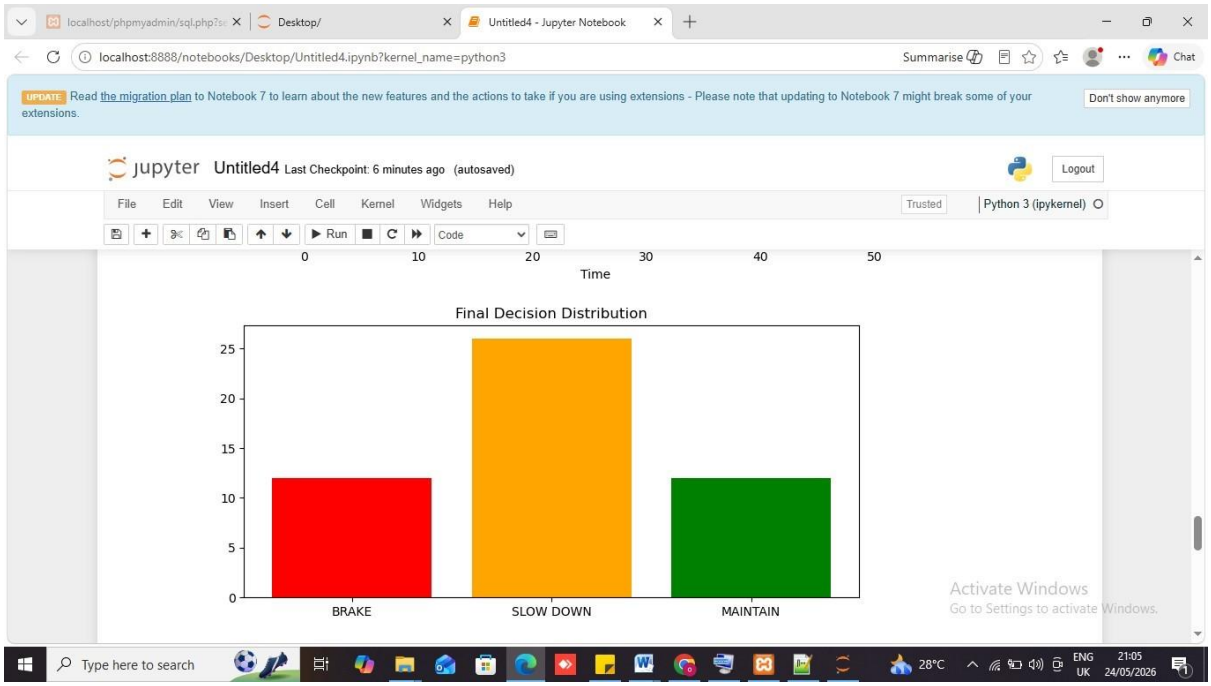
# APPENDIX B

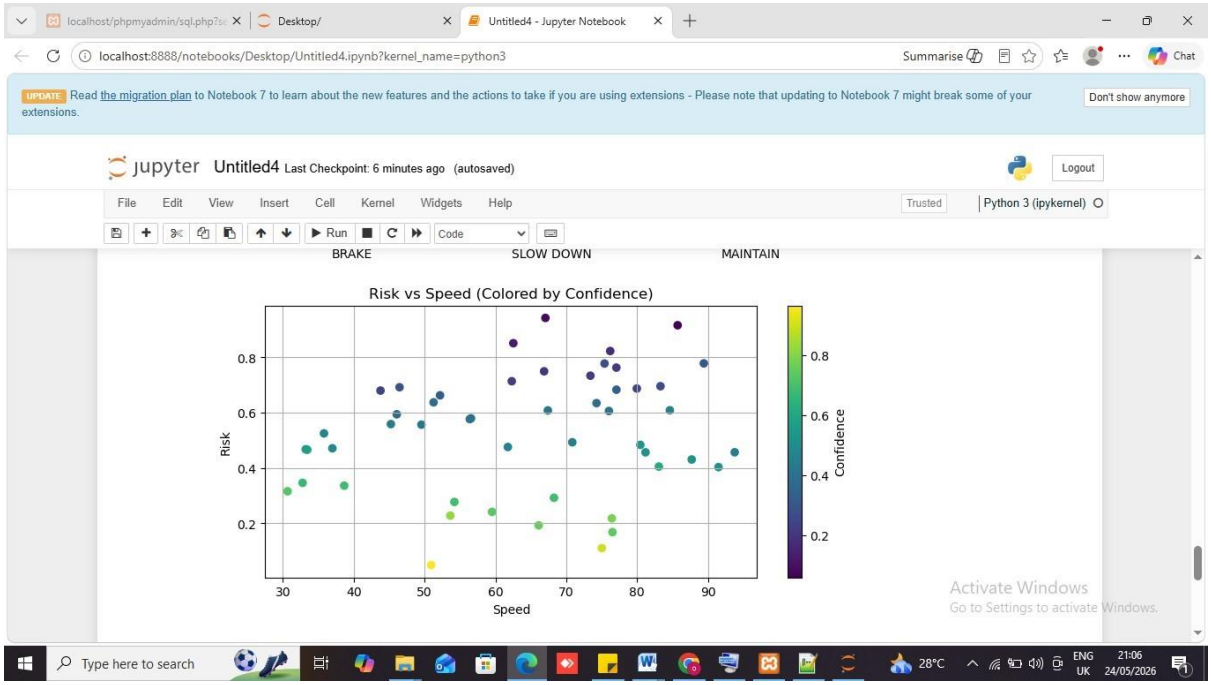
# SAMPLE OUTPUT

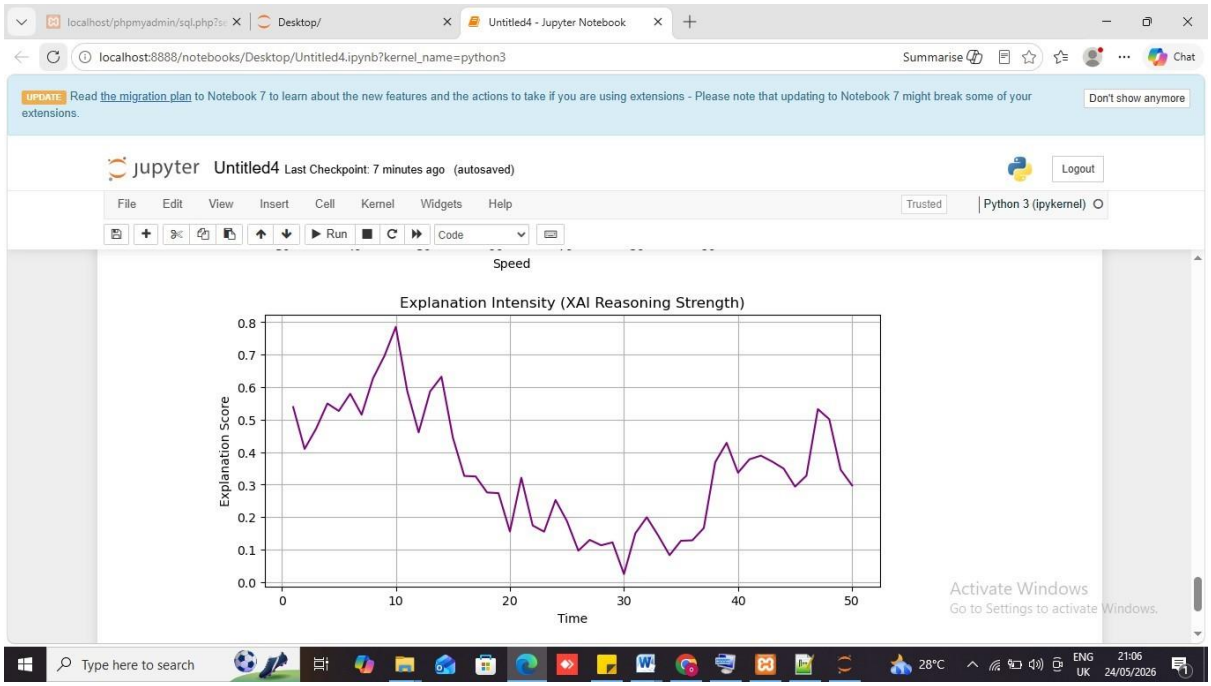


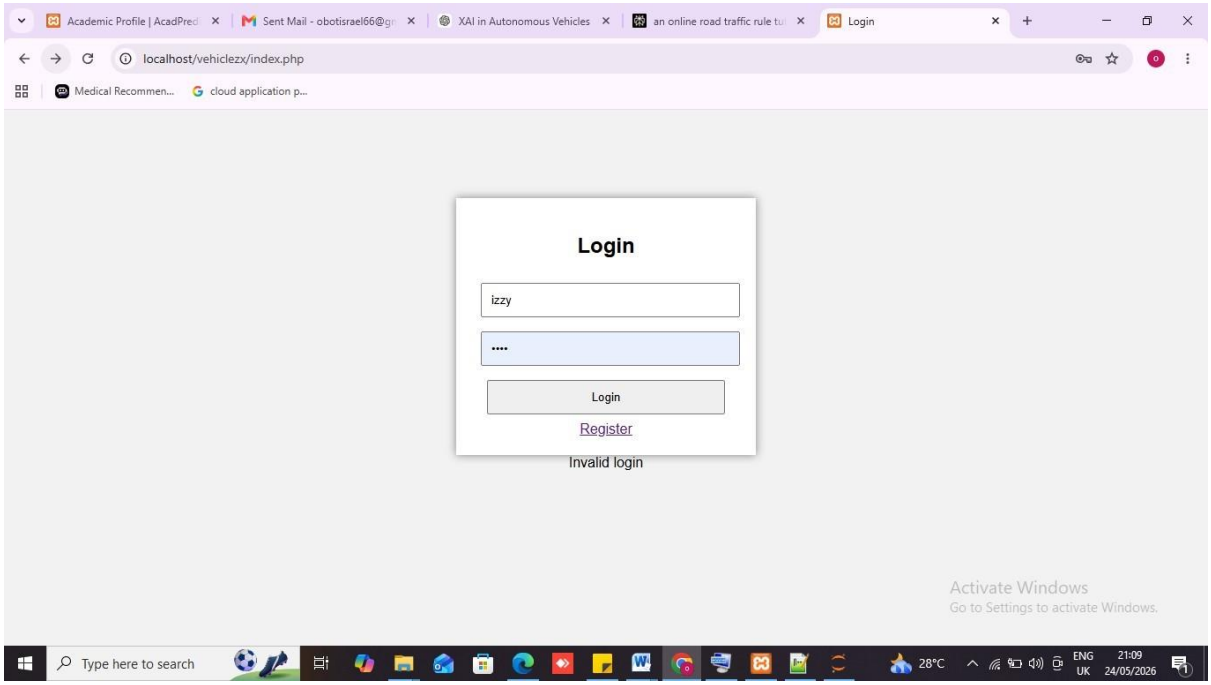

Untitled4 - Jupyter Notebook
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Read the migration plan to Notebook 7 to learn about the new features and the actions to take if you are using extensions - Please note that updating to Notebook 7 might break some of your extensions.
Don't show anymore
jupyter Untitled4 Last Checkpoint: 5 minutes ago (autosaved)
Logout
File Edit View Insert Cell Kernel Widgets Help
Trusted
Python 3 (ipykernel)
Run
Code
Time
Decision Timeline (XAI Output)
MAINTAIN
SLOW
BRAKE
0
10
20
30
40
50
Time
Activate Windows
Go to Settings to activate Windows.
Type here to search
ENG
UK
21:04
24/05/2026

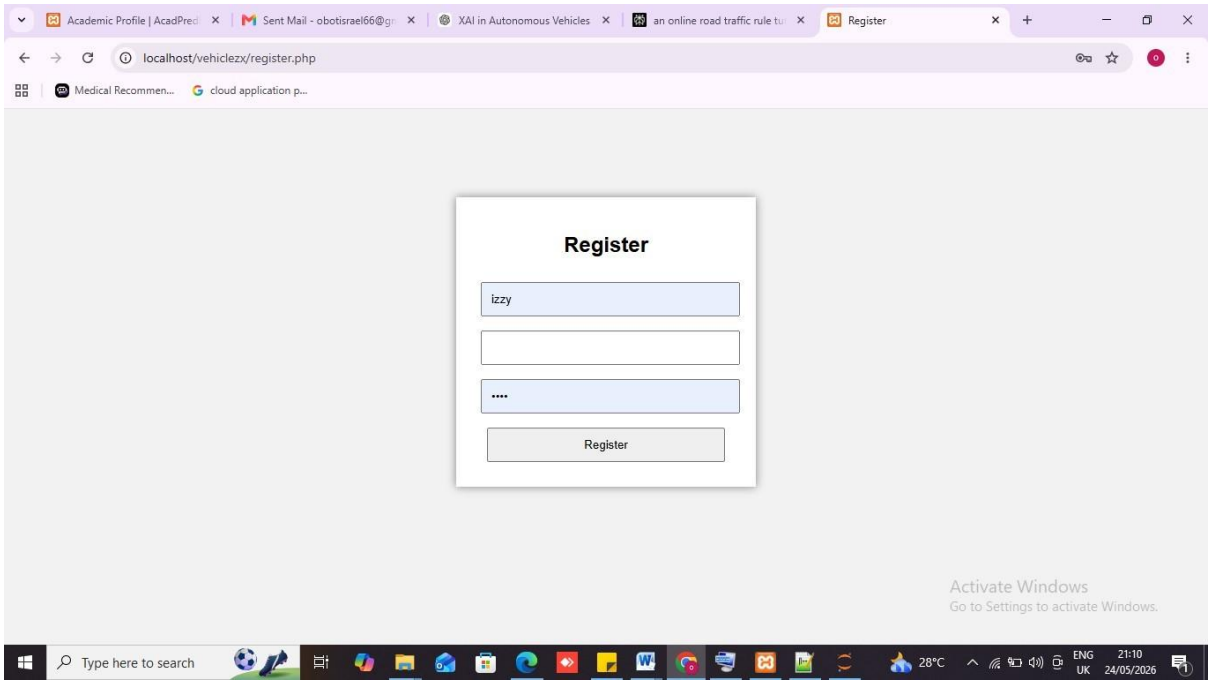
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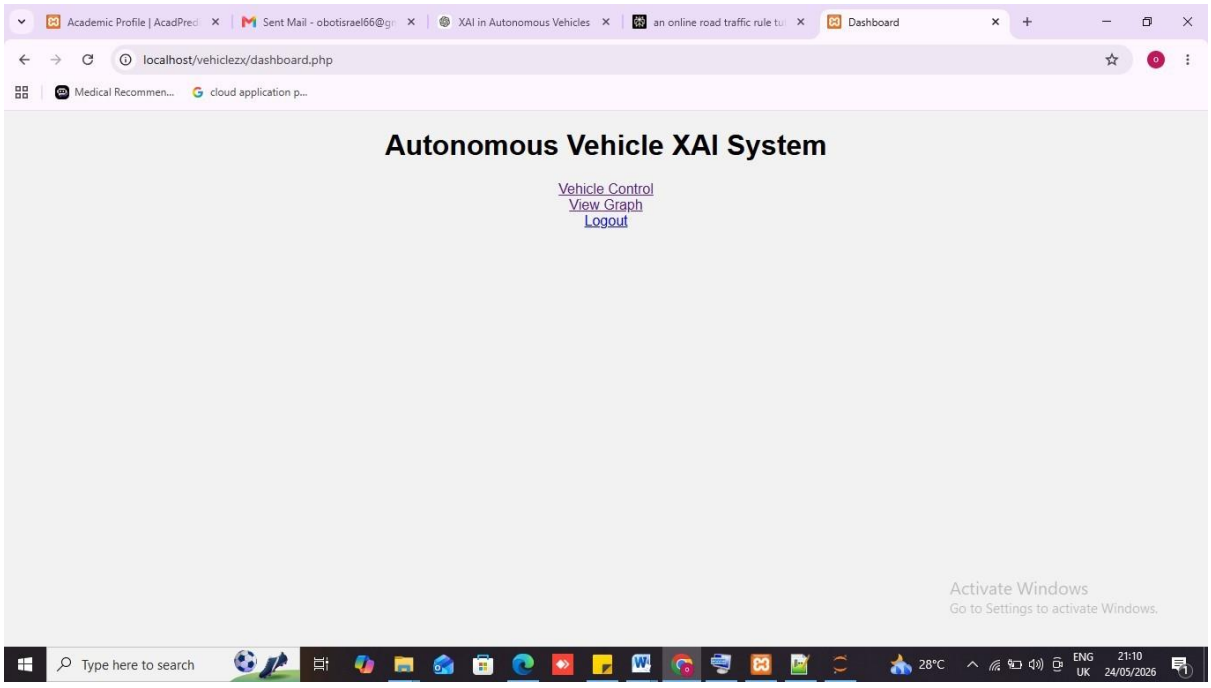

Time
Final Decision Distribution
BRAKE
SLOW DOWN
MAINTAIN

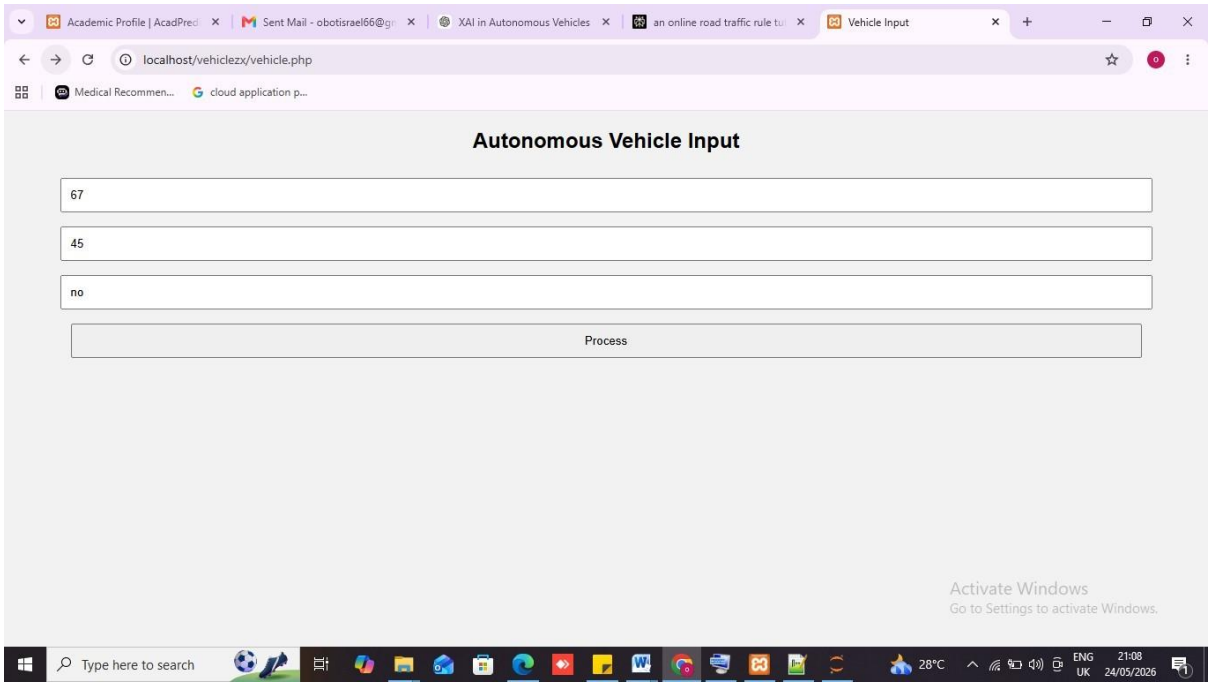

BRAKE
SLOW DOWN
MAINTAIN
Risk vs Speed (Colored by Confidence)
Risk
Speed
Confidence


Untitled4 - Jupyter Notebook
localhost:8888/notebooks/Desktop/Untitled4.ipynb?kernel_name=python3
Untitled4 Last Checkpoint: 7 minutes ago (autosaved)
Logout
File Edit View Insert Cell Kernel Widgets Help
Trusted
Python 3 (ipykernel)
Run
Code
Speed
Explanation Intensity (XAI Reasoning Strength)
Explanation Score
Time
0.0 0.1 0.2 0.3 0.4 0.5 0.6 0.7 0.8
0 10 20 30 40 50
Activate Windows
Go to Settings to activate Windows.
Type here to search
28°C
ENG UK
21:06
24/05/2026


localhost/vehiclezx/index.php
Login
izzy
Login
Register
Invalid login
Activate Windows
Go to Settings to activate Windows.
Type here to search
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ENG UK
21:09
24/05/2026


Register
localhost/vehiclezx/register.php
Register
izzy
Register
Activate Windows
Go to Settings to activate Windows.
Type here to search
28°C
ENG
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21:10
24/05/2026


Dashboard
localhost/vehiclezx/dashboard.php
Autonomous Vehicle XAI System
Vehicle Control
View Graph
Logout
Activate Windows
Go to Settings to activate Windows.
Type here to search
28°C
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UK
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24/05/2026


Academic Profile | AcadPred
Sent Mail - obotisrael66@gr
XAI in Autonomous Vehicles
an online road traffic rule tu
Vehicle Input
localhost/vehiclezx/vehicle.php
Medical Recommen...
cloud application p...
Autonomous Vehicle Input
67
45
no
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Activate Windows
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