A Bayesian Learning Framework Powered by IoT for Enhancing Highway Safety and Reducing Accidents: A Case Study of Benin-Onitsha Express Way

Jonathan Ebube Jibunor[1*], Benison Blessing Odigie [2], Olamotse Roland Igbape [3]

[1] Department of Computer Science, National Open University of Nigeria, Jabi, Abuja, Nigeria

[2] Department of Computer Science, Edo State University, Uzairue, Iyamho, Edo State, Nigeria.

[3] Department of Computer Science, Georgia Institute of Technology, Atlanta, USA.

***Corresponding Author**

DOI: https://doi.org/10.51584/IJRIAS.2024.910032

Received: 10 October 2024; Accepted: 15 October 2024; Published: 15 November 2024

ABSTRACT

The problem of frequent accidents on the Benin-Onitsha Express Way in Nigeria expressway necessitated the development of a predictive system that can enhance road safety. To address this issue, the study employed a framework that leverages real-time data collection from vehicles and road conditions to predict accident risks and deliver timely warnings to drivers. The methodology involved analyzing three years of historical accident data to identify high-risk areas and develop a cost-effective IoT model utilizing Bayesian learning techniques. The framework incorporated ESP8266-based client devices installed in vehicles, which gathered information on location, speed, and road conditions. This data was transmitted to a central server via Wi-Fi or GSM for analysis. The IoT platform ThingSpeak was utilized for data storage and visualization, facilitating real-time monitoring of vehicle locations and accident risk intensity. Results from the study demonstrated that the Bayesian model effectively identified accident-prone locations, achieving an area under the receiver operating characteristic curve (AUC-ROC) of 0.82, indicating excellent discrimination between high-risk and low-risk areas. The model achieved 75% precision and 80% recall, with a 15% false positive rate, which was deemed acceptable given the significant reduction in accidents observed. A comparative analysis revealed a decrease in reported accidents from 25 to 15 after system deployment, suggesting a positive impact on highway safety. Overall, the findings underscore the potential of integrating IoT and Bayesian learning for developing intelligent systems aimed at improving road safety and reducing accident rates on the Benin-Onitsha Express Way.

Keywords: Internet of Things (IoT), Bayesian Learning, Accident mitigation, Node MCU ESP8266, Thingspeak Platform

INTRODUCTION

Road traffic accidents are a major problem in developing countries, especially in Africa. These accidents have a huge economic impact, with estimates showing that they cost about 3% of a country's gross domestic product (Dhingra et al., 2021). The World Health Organization reports that 93% of all road accident deaths happen in low- and middle-income countries, even though they only have about 60% of the world's vehicles. Beyond the financial cost, these accidents also cause serious social issues, like the loss of lives and resources, which slows down progress in these societies (World Health Organization, 2020, Wang et al., 2023).

Many factors cause road accidents, including poor road conditions, driver fatigue, old vehicles, carelessness, using mobile phones while driving, and ignoring traffic rules (Fan et al., 2019, Liu, 2023, Zuo et al., 2024, Wang et al., 2017, Hamid et al., 2020, Dhingra et al., 2021). These issues highlight the need for ongoing education and awareness to reduce accidents (Mohseni et al., 2022, Bargahi et al., 2023, Cui & Lei, 2023, Nwankwo et al., 2019). Road accidents are also connected to broader social problems, such as human rights abuses, safety concerns, and limits on access to prosperity (Syafrudin et al., 2018). Researchers have pointed out the significant physical, social, and economic effects of road accidents (Nwankwo et al., 2022, Cui & Lei, 2023, Mohanta et al., 2022)

The causes of road accidents are complex, involving many different factors. In the past, efforts to prevent accidents have included new vehicle technologies, better road designs, and laws to improve road safety (Bargahi et al., 2023, Alnashwan et al., 2023, Sohail et al., 2023). Traditional methods, like better junction layouts, pedestrian crossings, and speed limits, have also played a role in reducing accidents (Wadhahi et al., 2018, World Bank, 2018, Liu & Ke, 2023, Sohail et al., 2023, Xue et al., 2023, Ruchin, 2018)

Despite these efforts, road accidents and deaths are still on the rise (Gopalan et al., 2024). Traditional methods face many challenges, such as people ignoring traffic signs, poor driver training, reckless driving—especially among young drivers—and mechanical problems like brake failures and tire bursts (Liu & Ke, 2023, Millicent et al., 2020). The use of fake spare parts makes these issues worse. There is a clear need for more advanced and effective ways to prevent accidents, and technology-based solutions could greatly improve safety and reduce accidents (Das et al., 2017).

In recent years, various technologies for monitoring vehicles and preventing accidents have been developed (Truong, 2020, Ruchin, 2018, Oluwaseyi & Gbadamosi, 2017, Xiao et al., 2023, Devarajan et al., 2024). These include systems like GPS, GIS, GSM, GPRS, image processing, fuzzy logic, data fusion, IoT-based wireless sensor networks, and hybrid positioning systems. Other useful technologies include those that monitor drivers, radar sensors, Intelligent Speed Adaptation (ISA), and Advanced Driver Assistance Systems (ADAS) (Fan et al., 2019, Kaur et al., 2023, Goniewicz et al., 2015). More recently, IoT and Artificial Intelligence (AI) have emerged as promising solutions for reducing road accidents. These cutting-edge technologies could offer the latest tools to help prevent and control accidents (Kaur et al., 2023, Goniewicz et al., 2015, Harum, 2016)

The Internet of Things (IoT) refers to devices that communicate with each other using the internet or other networks (Xue et al., 2023). IoT allows data from remote devices to be stored in the cloud, making it easy to access. These devices often include sensors and actuators that gather and transmit data (Ammar et al., 2018, Nwankwo et al., 2019, Babaitha et al., 2020, Kong et al., 2015). Using cloud technology provides safer data storage, unlimited access, data analysis, and better security. Cloud technology offers flexible services and the ability to share resources efficiently. Overall, IoT connects devices, systems, and services in ways that go beyond traditional machine-to-machine communication, covering a wide range of applications. IoT can be applied in many areas, including transportation, where it could help create smarter, safer systems (Liu, 2023, Francois-Lavet et al., 2018, Sai et al., 2020, Sarasvathi et al., 2018). The term "things" in IoT refers to a wide variety of devices, from heart monitoring implants to cars with built-in sensors (Victor et al., 2015, Coffin et al., 2019). IoT enables direct communication between machines, including vehicles and related systems, which could lead to safer roads. Given the growing problem of road safety in developing countries, IoT and AI offer great potential to improve road safety if used correctly (Nanda et al., 2018, Javadi et al., 2018, Bagga et al., 2021, Kheder & Mohammed, 2022)

Technological advancements have already led to various vehicle monitoring systems aimed at reducing accidents. Innovations like GPS, GIS, and IoT-based solutions are helping to improve road safety (Lv & Shang, 2023, Imteaj, 2015, Navod & Bindu Tushara, 2018, Muthusamy et al., 2015, Whig et al., 2024, Gohar & Nencioni, 2021, Niu et al., 2024). The combination of IoT and AI provides new ways to address traffic safety problems. IoT devices allow real-time data collection and analysis, helping authorities make better decisions in managing traffic (Pathik et al., 2022, George et al., 2017, Millicent et al., 2020). By using cloud technology, IoT applications can improve how data is stored, analyzed, and visualized, which enhances road safety efforts overall (Liyanage & Rengarasu, 2015, Vempaty & Kanakala, 2020, Maria et al., 2020, Pourghebleh et al., 2022, Zuo et al., 2024)

REVIEW OF RELEVANT STUDIES

The integration of Internet of Things (IoT) technologies with Bayesian learning systems presents a promising avenue for enhancing accident mitigation on highways. By leveraging real-time data collection and advanced analytical techniques, these systems can significantly improve the prediction and prevention of traffic incidents. This review synthesizes key studies that contribute to this field, highlighting their methodologies, findings, and implications for future research.

In their study titled IoT-Driven Bayesian Learning, A Case Study of Reducing Road Accidents of Commercial Vehicles on Highways, Nwankwo et al. (2022) explore the application of the Internet of Things (IoT) combined with Bayesian learning to minimize road accidents involving commercial vehicles on highways. The research, published in the book Artificial Intelligence-based Internet of Things Systems, investigates how IoT devices can be integrated with AI-driven systems to predict and prevent accidents by analyzing real-time data from vehicles. The authors utilized Bayesian learning algorithms to process this data, enabling the system to identify high-risk scenarios and make informed decisions to prevent accidents. Their case study highlights the potential of IoT and AI technologies in improving road safety, particularly for commercial vehicles, and emphasizes the importance of adopting smart technologies in transportation systems to reduce accident rates.

In the preprint titled "IoT Based Accident Prevention System Using Machine Learning Techniques," the authors, Alnashwan et al. (2023) from King Saud University present an innovative approach to predicting car accident severity influenced by adverse weather conditions. Recognizing that the likelihood of accidents increases during extreme weather events, the study proposes an Internet of Things (IoT)-based system utilizing three machine learning methods—Random Forest, LightGBM, and XGBoost—to forecast accident severity based on various weather features. The research employs a comprehensive dataset comprising 2.8 million vehicle accidents in the United States from 2016 to 2021, addressing the common issue of limited data in previous studies. Results indicate that LightGBM outperforms the other methods, achieving a prediction accuracy of 72%, alongside precision, recall, and F1-scores of 70%, and an AUC of 0.86. The findings suggest that while the proposed methodology is effective, further optimization and the incorporation of Saudi datasets could enhance predictive capabilities. This study contributes significantly to the field of intelligent transportation systems by leveraging IoT and machine learning for accident prevention.

In their study, Pathik et al. (2022) addresses the urgent issue of increasing road accidents, which claim approximately 1.4 million lives annually, according to the World Health Organization. The authors propose a sophisticated accident detection and alert system that integrates the Internet of Things (IoT) and Artificial Intelligence (AI) to enhance emergency response times. The system utilizes an IoT kit to collect critical accident data—such as location and speed—which is then transmitted to the cloud. Here, a deep learning model validates the data and activates emergency services, thereby reducing delays in rescue operations. The approach employs ensemble transfer learning with dynamic weights to minimize false detection rates and generates a personalized dataset from available online videos due to a lack of existing datasets. Comparative analyses of ResNet and InceptionResnetV2 confirm that the latter achieves superior accuracy, highlighting its potential effectiveness in real-world applications. The validation of the model's performance on a toy car further underscores its feasibility in smart city environments.

In the critical review titled "Data-driven approaches for learning from accidents, Comparative analysis and future research," Niu et al. (2024) systematically examine 194 articles from the past decade, focusing on the application of data-driven methodologies in accident prevention within the safety science domain. The review highlights key aspects such as paradigm, model, data source, and purpose, revealing significant gaps in the current research landscape. Notably, the authors identify the absence of a systematic framework to guide the integration of Big Data in safety applications and emphasize the need for improved model interpretability and the incorporation of proactive data in accident analysis. The analysis also points out that safety-related data and domain knowledge require further integration, and several emerging data-driven techniques remain underexplored in this field. The authors propose future research directions aimed at aligning data-driven tasks with specific safety goals, thereby facilitating the adoption of advanced technologies for more effective accident analysis and prevention. This review serves as a pivotal resource for understanding the current challenges and opportunities in leveraging machine learning and other data-driven approaches in safety science.

In the review article "IoT-Based Vision Techniques in Autonomous Driving," Kheder and Mohammed (2022) explore the integration of Internet of Things (IoT) technologies and computer vision in enhancing autonomous driving systems. The authors highlight the escalating incidence of road traffic accidents and the corresponding demand for innovative solutions to mitigate their effects. They emphasize that autonomous driving, supported by advanced embedded systems, can significantly enhance transportation safety by providing essential traffic information and protective measures for vehicle occupants. The review discusses the successful application of visual technologies and driver assistance systems, which collectively aim to reduce accidents, congestion, and pollution. Furthermore, the paper underscores the critical role of accurate environmental detection through static images and videos, facilitated by IoT connectivity and effective data management. By synthesizing findings from various reputable sources, Kheder and Mohammed provide a comprehensive overview of recent advancements in vision strategies and IoT applications, positioning them as pivotal to the future of autonomous driving and traffic safety.

Sohail et al. (2023) examine the critical challenges and advancements in enhancing road safety through data-driven methodologies. Highlighting the alarming statistic of over a million lives lost annually due to road accidents, the authors underscore the urgency for researchers and transport engineers to innovate safety measures. The review focuses on the increasing utilization of sensor technologies and the emergence of machine learning and deep learning techniques that have transformed road safety research in recent years. Addressing the multifaceted nature of road safety, which encompasses road infrastructure, user behavior, and traffic conditions, the authors propose a structured taxonomy to categorize data sources, sensors, and analytical methodologies. By analyzing key techniques that have shown promise in improving various road safety aspects, the paper identifies significant outcomes from existing studies. Furthermore, it discusses prevailing challenges in the field and suggests potential future research directions, providing valuable insights for advancing data-driven approaches to road safety and accident prevention.

Lu and Wang (2024) explore the intersection of the Internet of Things (IoT) and Intelligent Transportation Systems (ITS), emphasizing their potential to enhance the efficiency, safety, and sustainability of transport networks. The authors identify significant security challenges that arise from integrating IoT with ITS, which are crucial for the reliability of these systems. Through a thorough review methodology that includes literature analysis and expert interviews, the study highlights key achievements in the field while pinpointing critical security vulnerabilities. The findings indicate that despite advancements in securing ITS, challenges related to scalability, interoperability, and real-time data processing persist. The authors propose enhanced security protocols and strategies to mitigate these risks, thereby contributing to the development of more secure and resilient IoT-enabled ITS. This comprehensive analysis underscores the transformative potential of IoT in transportation, while also calling attention to the pressing need for effective security measures to safeguard these innovative systems.

In the study conducted by Liu (2023), a novel Quality of Service (QoS)-aware resource allocation method for the Internet of Things (IoT) is proposed, utilizing triplet and heterogeneous earliest finish time algorithms. The research addresses the critical challenge of resource allocation in IoT environments, where diverse applications demand varying levels of service quality. Liu's approach integrates triplet algorithms, which enhance the efficiency of resource distribution by considering multiple factors simultaneously, and heterogeneous earliest finish time algorithms, which optimize task scheduling based on the specific capabilities of different devices within the network. The empirical results demonstrate that this method significantly improves resource utilization and QoS metrics compared to traditional allocation strategies. The findings suggest that the proposed framework not only enhances the performance of IoT systems but also contributes to the sustainability of resource management in increasingly complex network environments. This work is a significant step towards developing more adaptive and efficient resource allocation mechanisms in IoT, highlighting the importance of tailored approaches to meet the unique demands of various applications in this rapidly evolving field.

In their comprehensive review, Soori et, al. (2023) explore the transformative role of the Internet of Things (IoT) in smart factories within the context of Industry 4.0. The authors systematically analyze various IoT technologies and their applications in enhancing operational efficiency, productivity, and flexibility in manufacturing processes. They highlight key components such as sensors, actuators, and data analytics, which facilitate real-time monitoring and decision-making, thereby enabling a more responsive manufacturing environment. The review also discusses the challenges associated with IoT implementation, including security concerns, interoperability issues, and the need for robust infrastructure to support the vast amount of data generated.

Furthermore, the authors emphasize the importance of integrating IoT with other emerging technologies, such as artificial intelligence and machine learning, to fully realize the potential of smart factories. By synthesizing current research and practical applications, this review provides valuable insights for researchers and practitioners aiming to leverage IoT technologies in the evolution of manufacturing systems, ultimately contributing to the advancement of Industry 4.0 initiatives.

In their article, Kaur et al. (2023) provide a thorough examination of the evolution of security datasets for the Internet of Things (IoT), addressing the significant challenges and proposing future directions for research in this critical area. The authors categorize various types of IoT security datasets, emphasizing their importance in developing effective machine learning models for intrusion detection systems. They highlight the rapid growth of IoT devices and the corresponding increase in security threats, which necessitates the continuous evolution of security datasets to keep pace with emerging attack vectors. The paper identifies key challenges, including the lack of standardized datasets, the need for diverse and representative data to train models effectively, and the difficulties in simulating real-world attack scenarios. Furthermore, the authors propose future research directions, such as the development of more comprehensive datasets that incorporate various attack types and the integration of advanced machine learning techniques to enhance detection capabilities. This work underscores the critical need for robust security measures in IoT environments and serves as a foundational reference for researchers aiming to advance the field of IoT security through improved dataset utilization and development.

In their comprehensive review, Lv and Shang (2023) investigate the impacts of intelligent transportation systems (ITS) on energy conservation and emission reduction within transport systems. The authors systematically analyze various ITS technologies and their effectiveness in enhancing the efficiency of transportation networks. Key findings indicate that ITS can significantly reduce fuel consumption and greenhouse gas emissions through improved traffic management, real-time data sharing, and optimized routing. The review highlights several critical components of ITS, including adaptive traffic signals, vehicle-to-everything (V2X) communication, and smart parking solutions, which collectively contribute to more sustainable urban mobility. Furthermore, the authors discuss the challenges associated with implementing ITS, such as the need for substantial investment in infrastructure, data privacy concerns, and the integration of diverse technologies. They also emphasize the importance of policy frameworks and stakeholder collaboration in maximizing the benefits of ITS for energy conservation and emission reduction. Overall, this review provides valuable insights into the potential of intelligent transportation systems to foster sustainable transport solutions and outlines future research directions to enhance their effectiveness in mitigating environmental impacts.

In their study, Bargahi et al. (2023) explore the intricate relationship between criticality and travel time reliability in transportation networks, presenting their findings at the 2023 IEEE 26th International Conference on Intelligent Transportation Systems. The authors define criticality as a measure of the importance of network components, which can significantly influence the overall performance and reliability of transportation systems. They emphasize that understanding this relationship is crucial for enhancing the efficiency and resilience of transportation networks, particularly in urban settings where congestion and delays are prevalent.

In their study, Zuo et al. (2024) propose a security-enhanced privacy-preserving data aggregation scheme specifically designed for intelligent transportation systems (ITS). The authors address the critical need for secure data handling in ITS, where sensitive information from vehicles and infrastructure is collected and processed. Their proposed scheme integrates advanced cryptographic techniques to ensure data privacy while enabling efficient aggregation, which is essential for real-time decision-making in transportation networks.

In their article, Devarajan et al. (2024) present a novel imaging methodology aimed at enhancing intelligent transportation systems (ITS) within the consumer industry. The authors emphasize the critical role of advanced imaging technologies in improving traffic management, safety, and user experience in urban environments.

Wang et al. (2023) present a comprehensive exploration of "Transportation 5.0," focusing on the integration of decentralized autonomous organizations (DAOs) to enhance the safety, security, and sustainability of intelligent transportation systems (ITS). The authors argue that traditional transportation frameworks are increasingly challenged by issues related to safety, security, and environmental sustainability, necessitating a transformative approach.

Cui and Lei (2023) present a comprehensive design framework for a highway intelligent transportation system (ITS) that leverages the Internet of Things (IoT) and artificial intelligence (AI) to enhance traffic management and safety. The authors emphasize the integration of IoT devices, such as sensors and cameras, to collect real-time data on traffic conditions, vehicle behavior, and environmental factors. This data is then processed using AI algorithms to facilitate intelligent decision-making, enabling dynamic traffic control and improved incident response. The study outlines several key components of the proposed ITS, including vehicle-to-everything (V2X) communication, which enhances connectivity between vehicles and infrastructure, and predictive analytics that optimize traffic flow and reduce congestion. Additionally, the authors address challenges related to data security and privacy, proposing solutions to ensure the safe handling of sensitive information. Overall, the research highlights the potential of combining IoT and AI technologies to create more efficient, responsive, and safer highway transportation systems, paving the way for future advancements in smart mobility.

Pourghebleh et al. (2022) provide a detailed roadmap for developing energy-efficient data fusion methods in the Internet of Things (IoT), addressing the critical challenge of energy consumption in IoT devices that often operate on limited power sources. The authors systematically review existing data fusion techniques, highlighting their strengths and weaknesses in terms of energy efficiency and performance. They propose a framework that emphasizes the importance of optimizing data processing and transmission to minimize energy usage while maintaining the accuracy and reliability of the information collected. The study also discusses various factors influencing energy efficiency, including the choice of algorithms, the architecture of IoT systems, and the nature of the data being processed. By identifying key research gaps and suggesting future directions, the authors aim to guide researchers and practitioners in developing more sustainable data fusion methods that can enhance the overall performance of IoT applications. This work contributes to the ongoing discourse on energy efficiency in IoT, underscoring the need for innovative approaches to manage energy consumption effectively in increasingly complex networked environments.

Whig et al. (2024) explore the transformative role of artificial intelligence (AI) and the Internet of Things (IoT) in the development of intelligent transportation systems (ITS). The authors emphasize that the integration of AI and IoT technologies is pivotal for enhancing the efficiency, safety, and sustainability of transportation networks. They discuss various applications of AI, such as predictive analytics for traffic management, autonomous vehicles, and real-time monitoring systems that leverage IoT devices to collect and analyze data from the transportation environment. The chapter highlights the potential of these technologies to reduce human error in driving, optimize traffic flow, and improve overall user experience in urban mobility. Furthermore, the authors address the challenges associated with implementing AI and IoT in transportation, including data privacy concerns, cybersecurity risks, and the need for robust infrastructure to support these advanced technologies. By providing a comprehensive overview of the current state and future directions of AI and IoT in intelligent transportation, Whig et al. contribute valuable insights for researchers and practitioners aiming to advance smart mobility solutions.

Mohanta et al. (2022) investigate the application of machine learning techniques for accident prediction within a secure Internet of Things (IoT)-enabled transportation system. The authors emphasize the critical need for effective accident prediction models to enhance road safety and reduce the frequency of traffic incidents. They propose a framework that integrates various machine learning algorithms to analyze real-time data collected from IoT devices, such as sensors and cameras, which monitor traffic conditions and driver behavior. The study evaluates the performance of different algorithms, including decision trees, support vector machines, and neural networks, in predicting accidents based on historical data and real-time inputs. The results demonstrate that the machine learning models significantly improve the accuracy of accident predictions, enabling timely interventions to prevent potential incidents. Additionally, the authors address the importance of ensuring data security and privacy in IoT systems, highlighting the need for robust security measures to protect sensitive information. Overall, this research contributes to the advancement of intelligent transportation systems by providing a data-driven approach to accident prediction, ultimately aiming to enhance road safety and operational efficiency.

Liu and Ke (2023) explore the integration of cloud-assisted Internet of Things (IoT) technologies within intelligent transportation systems (ITS) and traffic control systems in smart cities. The authors highlight the potential of cloud computing to enhance the efficiency and effectiveness of transportation management by enabling real-time data processing and analysis from various IoT devices deployed throughout urban environments. Their study discusses the architecture of a cloud-assisted ITS, which facilitates seamless communication between vehicles, infrastructure, and traffic management centers, thereby improving traffic flow and reducing congestion. The authors also examine the role of advanced analytics and machine learning algorithms in optimizing traffic control strategies, allowing for adaptive responses to changing traffic conditions. Through empirical analysis, the research demonstrates that the proposed cloud-assisted framework significantly enhances traffic management capabilities, leading to improved safety and reduced travel times. Overall, Liu and Ke's work contributes to the understanding of how cloud computing and IoT can be leveraged to create smarter, more responsive transportation systems in urban settings, ultimately supporting the development of sustainable smart cities.

Verma et al. (2021) investigate intelligent and secure clustering techniques in wireless sensor networks (WSNs) specifically tailored for intelligent transportation systems (ITS). The authors emphasize the importance of clustering in WSNs to enhance data aggregation and communication efficiency, which are critical for real-time traffic management and safety applications. Their study introduces a novel clustering algorithm that not only optimizes energy consumption but also incorporates security measures to protect sensitive data transmitted within the network.

Yuvaraj et al. (2022) conduct a comprehensive investigation into garbage disposal electric vehicles (GDEVs) integrated with deep neural networking (DNN) and intelligent transportation systems (ITS) within the framework of smart city management systems (SCMS). The study addresses the limitations of conventional smart city management approaches, which often rely on basic sensor or IoT technologies without effectively managing the routing and scheduling of electric vehicles for waste collection.

Bagga et al. (2021) present a comprehensive design for a mutual authentication and key agreement protocol tailored for Internet of Vehicles (IoV)-enabled intelligent transportation systems (ITS). The authors highlight the critical need for secure communication among vehicles and infrastructure to prevent unauthorized access and ensure data integrity in ITS environments. Their proposed protocol employs a lightweight cryptographic approach that facilitates mutual authentication between vehicles and roadside units, thereby enhancing security without compromising performance.

Dhingra et al. (2021) investigate the application of Internet of Things (IoT)-based fog and cloud computing technologies for smart traffic monitoring, emphasizing their potential to enhance traffic management and improve urban mobility. The authors propose a framework that integrates fog computing, which processes data closer to the source, with cloud computing, which offers extensive storage and computational resources. This hybrid approach allows for real-time data collection and analysis from various IoT devices deployed in traffic environments, such as sensors and cameras.

Gohar and Nencioni (2021) explore the transformative potential of 5G technologies in smart cities, specifically focusing on Intelligent Transportation Systems (ITS). They emphasize that 5G provides the essential communication infrastructure necessary for various smart city applications, enabling enhanced connectivity and efficiency. The authors detail how 5G's capabilities, such as high data rates, low latency, and support for a massive number of connected devices, are crucial for the development of ITS, which in turn can optimize urban transportation, reduce congestion, and improve overall sustainability. They also discuss the economic implications of integrating 5G within vertical industries like energy, healthcare, and automotive, highlighting the significant benefits 5G can bring to urban management and service delivery. The paper ultimately argues that leveraging 5G in conjunction with IoT can significantly elevate the quality of life in urban environments by enabling smarter, more responsive city infrastructures.

Mohseni et al. (2022) present CEDAR, a cluster-based energy-aware data aggregation routing protocol designed for the Internet of Things (IoT), utilizing a combination of the Capuchin search algorithm and fuzzy logic. Their research addresses the critical challenge of energy efficiency in IoT networks by optimizing data aggregation processes to minimize energy consumption. The authors demonstrate that CEDAR effectively enhances network lifetime and data accuracy by intelligently forming clusters and employing a fuzzy logic approach to adaptively manage routing decisions based on real-time conditions. Through simulation results, they illustrate significant improvements in energy efficiency and overall network performance compared to existing protocols, underscoring the potential of their approach for future IoT applications.

Liu (2023) introduces an IoT-based multi-channel information integration method tailored for wireless sensor networks, aiming to enhance data processing and communication efficiency. The study addresses the challenges of information overload and interoperability in sensor networks by proposing a framework that integrates multiple data channels for streamlined information flow. Through empirical analysis, Liu demonstrates that the proposed method significantly improves data accuracy and reduces latency compared to traditional integration approaches. The results indicate that this multi-channel strategy not only optimizes resource utilization but also supports real-time decision-making in various IoT applications, highlighting its potential for advancing the functionality of wireless sensor networks.

Xue et al. (2023) present a novel cluster-based routing protocol for wireless sensor networks (WSN) enabled by the Internet of Things (IoT), leveraging the Water-Cycle Algorithm (WCA) to enhance energy efficiency. Their research addresses the critical challenge of energy consumption in IoT networks by proposing a clustering method that optimally organizes nodes in dense and heterogeneous environments. The authors demonstrate through simulation results that their proposed protocol, referred to as CC-WCA, significantly outperforms existing routing methods in terms of energy utilization, throughput, and network longevity. By integrating clustering with Software-Defined Networking (SDN) principles, the study highlights the potential of CC-WCA to improve overall network performance and sustainability in IoT applications, marking a substantial advancement in routing protocol design for resource-constrained environments.

Xiao et al. (2023) investigate a novel reliability evaluation method for large-scale intelligent transportation wireless sensor networks, employing tensor and confident information coverage approaches. The study addresses the critical issue of ensuring reliable data transmission in complex transportation environments by developing a framework that quantitatively assesses network reliability based on coverage metrics. Through extensive simulations, the authors demonstrate that their method effectively captures spatial and temporal variations in sensor coverage, leading to improved reliability assessments compared to traditional techniques. The results indicate that the proposed evaluation framework enhances the robustness of intelligent transportation systems, facilitating better decision-making and operational efficiency in real-time traffic management scenarios. This research contributes to the advancement of reliable communication protocols within the context of large-scale IoT applications in the transportation sector.

Gopalan et al. (2024) introduce a fuzzified swarm intelligence framework utilizing the FPSOR algorithm aimed at enhancing the performance of high-speed Mobile Ad Hoc Networks (MANET) within the Internet of Things (IoT) ecosystem. The study addresses the challenges of efficient data routing and resource management in dynamic and resource-constrained environments by incorporating fuzzy logic into swarm intelligence techniques. Through extensive simulations, the authors demonstrate that their FPSOR-based approach significantly outperforms traditional routing protocols in terms of latency, throughput, and energy efficiency. The results indicate that the fuzzified framework effectively adapts to varying network conditions, thereby improving the overall reliability and responsiveness of MANET-IoT integrations. This research contributes valuable insights into optimizing communication strategies for high-speed IoT applications, highlighting the potential of hybrid intelligent algorithms in addressing real-time operational challenges.

Quy et al. (2022) provide a comprehensive survey of routing algorithms specifically designed for Mobile Ad Hoc Networks (MANET) integrated with the Internet of Things (IoT). The authors systematically categorize existing routing protocols based on their underlying mechanisms, including proactive, reactive, and hybrid approaches, while critically evaluating their performance in various scenarios. Through an extensive review of recent literature, the study highlights key challenges facing MANET-IoT networks, such as dynamic topology changes, limited bandwidth, and energy constraints. The authors also discuss the effectiveness of advanced techniques, including machine learning and swarm intelligence, in enhancing routing efficiency and reliability. This survey serves as a valuable resource for researchers and practitioners seeking to understand the current state of routing solutions in MANET-IoT environments and outlines future research directions to address existing gaps.

The reviewed studies underscore the potential of IoT-driven systems, particularly when combined with Bayesian learning techniques, to significantly enhance accident mitigation on highways. By leveraging real-time data and advanced analytical methods, these systems can improve the accuracy of accident detection, facilitate timely responses, and ultimately contribute to safer road environments. Future research should focus on integrating these technologies to develop more adaptive, intelligent systems capable of addressing the complexities of modern transportation networks.

MATERIALS AND METHOD

The approach used for this study is the case study approach, focusing on the Benin-Onitsha Highway, a significant trunk A road in Nigeria. This highway is a primary segment of the A1 highway, which is one of the key highways in the country. It originates in Benin City and passes through several important locations, including Agbor, Asaba, Onitsha, Kaduna, Zaria, and Kano, before ending at Kongolam, located at the border with the Niger Republic. The Benin-Onitsha Highway serves as a crucial artery for trade and transportation, facilitating the movement of goods and people across various regions in Nigeria. Its condition and operational challenges have significant socio-economic implications for local communities and businesses, making it an important subject for analysis in understanding the broader impacts of infrastructure on economic activities and road safety in the region.

The historical highway accident data covering a 3-year period from first quarter of 2021 to first quarter of 2024 were collected from the Federal Road Safety Corps (FRSC) in Asaba, Delta State. The road which was segmented into 20 locations using marked differences such as height above sea level, width of road, traffic density, and distance from a reference point (Bridge Head Toll Gate, Asaba). The number of vehicles per hour within the segment was recorded as traffic density. Attention was on both injuries and fatal accidents for the male and female folks. The accident data includes; number of male and female accident victims, number of male and female injured victims and number of male and female deaths for the three consecutive years.

Accident prone areas, road condition, and the number of deaths (male and female) were taken from the accident data and used to map each location of the road to a level of proneness to accidents. The degree of proneness to accident was rated either low or high. This proneness is contextually regarded as the risk value and is represented with red (high) and low (green) in the prototype implementation (Nwankwo & Olayinka, 2019, Nwankwo et al. 2022).

The predictable target variable that will be defined by means of Bayesian learning, was taken as the risk associated with any vehicle travelling on the road at each point of the road.

Materials

The following materials were used: Breadboard and jumper wires, ESP8266-development board, SIM800L GSM, GPS-uBlox Neo 6M, 16×2 I2C LCD, Buzzer, Arduino IDE, Lipo Battery ufx102535, and Server-grade PC (HP intel (R) Celeron (R) CPU 3050, 1.6Ghz PC @ 2GB RAM), USB cables. For the prototyping, the thingspeak open IoT prototyping platform was used. However, a road safety coordinating base station with a 170m radio tower, situated around the Ekpoma area of the highway is proposed to holds a central analytics server system for live deployment.

Interfacing

The 16×2 I2C Liquid Crystal Display and ESP8266-12E Interfacing

Table 3.2 below shows the Inter-connection between the 16×2 I2C Liquid Crystal Display and NodeMCU, ESP8266-12E.

Table 3.2: Interfacing 16×2 I2C LCD and ESP8266-12E

ESP8266-12E	16×2 I2C LCD
D1	SCL
D2	SDA
G	GND
VU(5V)	VCC

The Circuit diagram of 16×2 I2C LCD and ESP8266-12E Interfacing

Fig. 3.1 below shows the circuit diagram for the interfacing of the Node MCU and the LCD

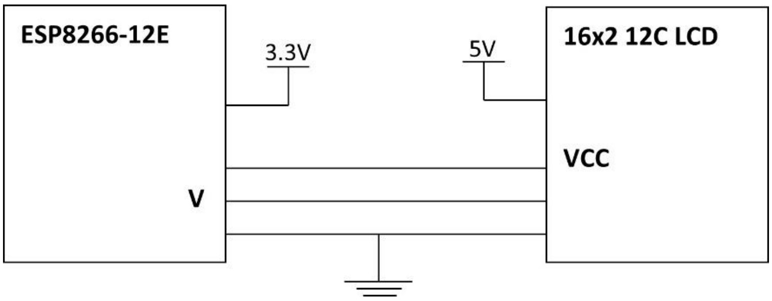


Fig. 3.1 Circuit diagram of 16×2 I2C LCD and ESP8266-12E Interfacing

The GPS UBlox Neo-6M and ESP8266-12E Interfacing

Table 3.3 below shows the Inter-connection between the GPS UBlox Neo-6M and ESP8266-12E.

Table 3.3: Interfacing GPS UBlox Neo-6M and ESP8266-12E

ESP8266-12E	GPS UBlox Neo-6M
D3	RX
D4	TX
G	GND
3V	VCC

Circuit diagram of GPS UBlox Neo-6M and ESP8266-12E Interfacing

Fig. 3.2 below shows the circuit diagram for the connection between the GPS UBlox Neo-6M and NodeMCU, ESP8266-12E.

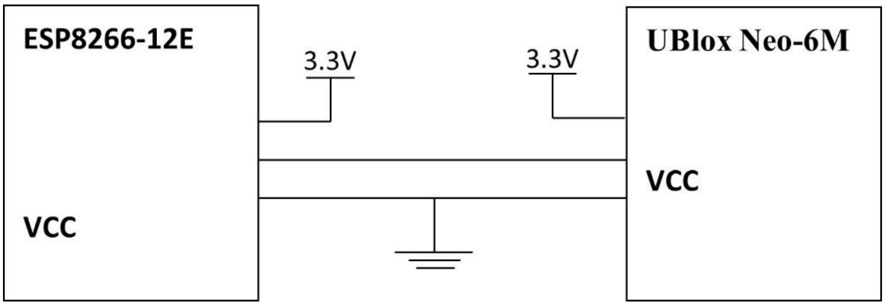


Fig. 3.2: Circuit Diagram of GPS UBlox Neo-6M and ESP8266-12E Interfacing

The SIM800L GSM, and ESP8266-12E Interfacing

Table 3.4 below shows the Inter-connection between the SIM800L GSM, and ESP8266-12E.

Table 3.4: Interfacing SIM800L GSM and ESP8266-12E

ESP8266-12E	SIM800L GSM
D5	RXD
D6	TXD
G	GND
Vcc	Vcc = 4v

Circuit Diagram of SIM800L GSM and ESP8266-12E Interfacing

Fig. 3.3 below shows the circuit diagram for the connection between the SIM800L GSM, and ESP8266-12E.

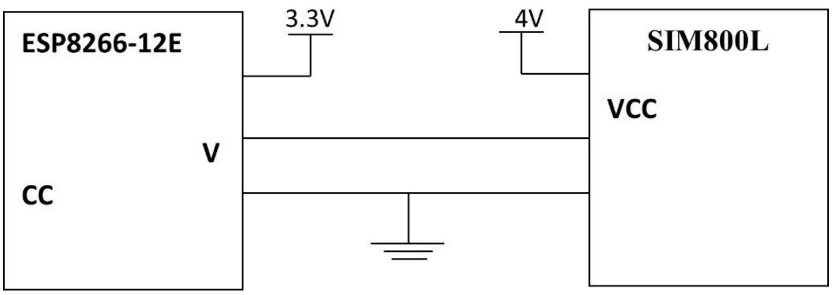


Fig. 3.3: Circuit Diagram of SIM800L GSM and ESP8266-12E Interfacing

The Buzzer and ESP8266 Interfacing

Table 3.5 below shows the Inter-connection between the Buzzer and NodeMCU, ESP8266-12E.

Table 3.5: Interfacing Buzzer and ESP8266-12E.

ESP8266-12E	Buzzer
D0	RED TERMINAL (+)
GND	BLACK TERMINAL (-)

Circuit diagram of Buzzer and ESP8266-12E Interfacing

Fig. 3.4 below shows the circuit diagram for the connection between the Buzzer and ESP8266-12E.

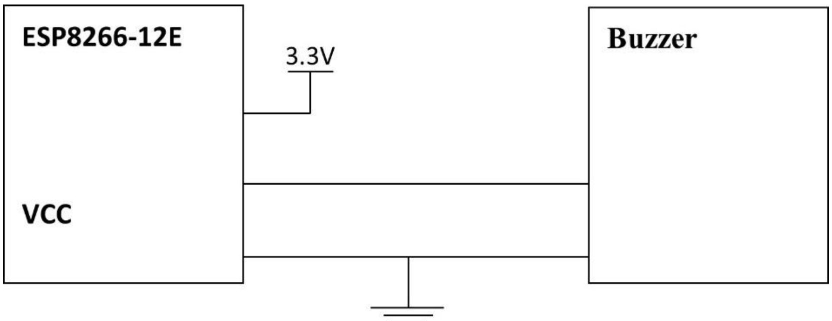


Fig. 3.4: Circuit Diagram of Buzzer and ESP8266-12E Interfacing

ISSN No. 2454-6194 | DOI: 10.51584/IJRIAS |Volume IX Issue X October 2024

Description of the Case Study

The Benin-Onitsha Expressway in Nigeria is a vital transportation route that connects Benin City in Edo State to Onitsha in Anambra State. This highway is part of the A1 road network and spans approximately 100 kilometers, facilitating trade and movement between the southern and eastern regions of Nigeria. Along its route, the expressway passes through several significant local councils, including Ovia South-West, Aniocha, Ika North-East, Ika South, and areas around Asaba in Delta State, as well as Onitsha North and Onitsha South in Anambra State. The expressway serves as a crucial corridor for commercial activities, characterized by a high volume of traffic from commercial vehicles, buses, and freight trucks transporting goods such as agricultural products and manufactured items. Known for its heavy usage, especially by vehicles carrying goods to and from major markets, the expressway ranks among the busiest highways in the region. However, road conditions can vary, and ongoing maintenance efforts aim to address issues like potholes and traffic congestion to enhance safety and efficiency for all users.

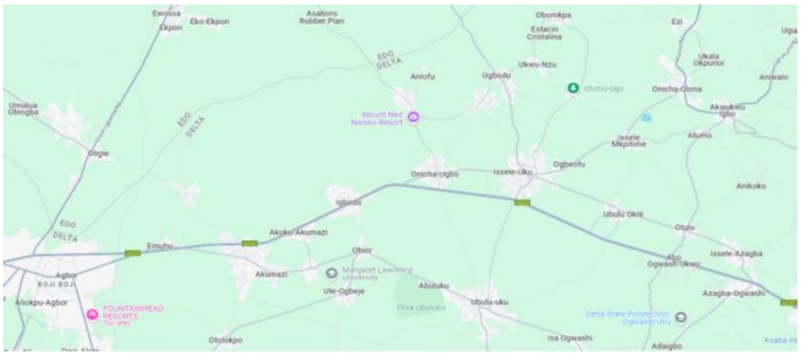


Fig. 3.5: Map showing Benin-Onitsha Express Way

Design approach

The system is divided into two components: the client device and the server. The client device resides in the vehicle and communicates with the server through the WIFI, and/or GSM and GPS. It also incorporates a register for storing manifest data and an audio device. The data is transmitted to the server (at a proposed coordinating location) where a proposed radio tower (mast) could be available to provide a long distance connectivity along the highway. A proposed LTE-compliant 5-20GHZ omni-radio could also reside on the tower and connects through a gateway to a web/analytics server and all communications from the recipient devices could be sent to the server through the radio tower. Fig. 3.6 shows the logical model of the design while Fig. 3.7 shows the schematic of the client device.

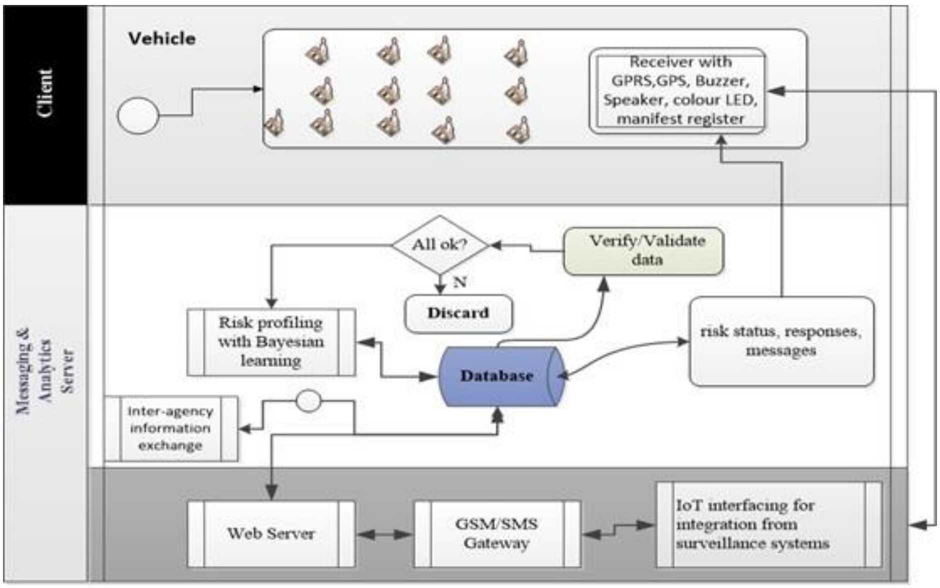


Fig. 3.6: Logical model of the proposed system.

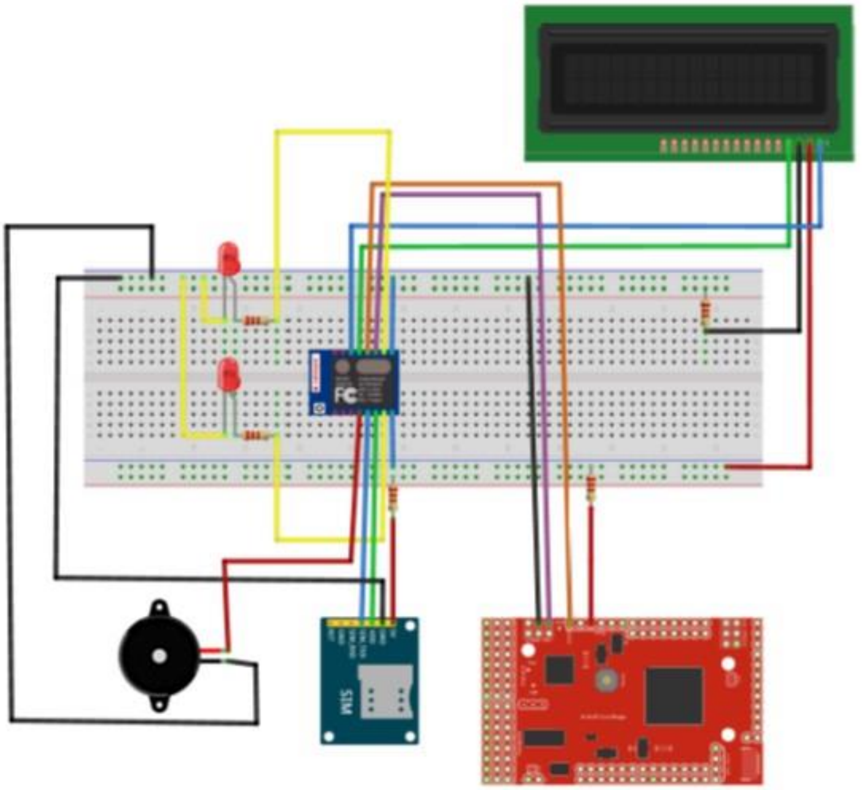


Fig. 3.7: Schematic of the client device

Data preprocessing and Feature selection

The accident dataset description and attributes are show in Table 3.6

Table 3.6: Description of selected variables in the dataset

S/N	Label	Description
1	Risk	**Target variable**
2	Date	Predictor representing day of accident e.g. sunday
3	number_motorists	Number of motorists in a commercial vehicle
4	Male	Number of males
5	Female	Number of females
5	injured_male	Injured males
6	injured_female	Injured females
7	male_fatality	Number of male fatalities
8	female_fatality	Number of female fatalities
9	road_segment_condition	Road status condition
10	Location	Location on the road at any time

The pre-processing addresses missing values and inconsistencies arising from out-of-range values e.g. (location: between Agbor and Issele-Ukwu; number of injured male: unsure; etc.). Feature selection was done to establish a correlation relationship between the target variable (risk) and the inputs in Table 3.6 and only variables adjudged to exhibit the strongest correlation were selected. The "date" attribute was disregarded owing to its loose relationship with the target variable. Road segment condition is highly correlated with female and male injured and female and male fatalities etc. This can be helpful in feature selection. It can help to prevent multicollinearity in linear models. However, the attributes: injured_male, injured_female, male_fatality, and female_fatality are not considered feasible attributes that could be easily computed in a non-chaotic system (free moving vehicle under no accident) hence not be used as inputs for the actual bayesian prediction. The other attributes such as number_of_ motorists, male, and female could be preset into the device from the passenger manifest at the commencement of a trip.

Bayesian Model Building and Testing

The Naïve Bayes algorithm is a requirement for this problem as the various predictors appear naturally self-governing. For example, there lack obvious relationship between the females and males in public transportation system. The same is correct for injured males and injured females as well as death rates. The primary bayesian rule is therefore to calculate a risk of accident: P(R|X), given the feature domain X (number_motorists = N, male = M, female = F, road_segment_condition = S, location = T).

Mathematically, P(R|X)=P(X|R)P(R)/P(R) (1)

The algorithm implemented to compute P(R|X) is:

1. Divide the dataset into the training set (80%) and test set(20%);
2. Determine attribute probabilities conditional on the class value;
3. Compute joint conditional probability for the attributes using the product rule;
4. Neglect attribute with missing values;
5. Where an attribute value does occur regularly with the class value, insert a probability of zero (0);
6. Use Bayes rule to calculate the conditional probabilities for the class variable
7. Compare the probabilities;
8. Compute the mean and standard deviation of the set
9. Return class with the highest probability
10. Apply results to a testing data set

Accuracy of the Machine Learning Model

Accuracy quantifies what number of predictions are coordinated precisely with the real or valid label of the testing dataset and if it returns the level of right outcomes. It could be calculated with the following equation:

$$Accuracy(y, y') = \frac{1}{x_{samples}} \sum_{i=0}^{x_{samples}-1} 1(y'_i = y_i) \quad \text{….. (2)}$$

The ration of correct prediction over a set x of sample data is defined by (Equation 2) above.

Where:

y'_I = Predicted value of the ith sample.

y_i = Corresponding true value.

IMPLEMENTATION

Here we are interfacing the GPS and SIM800L GSM with the ESP8266-12E Node MCU. The device also incorporated a 16x12 12C LCD for display. The GPS module would be used to identify the real-time location of the vehicle from anywhere and the SIM800L incorporated a SIM card for communication via text messaging and calls. The ThingSpeak IoT cloud would be used to store the history of accident prone locations and associated data from Bayesian learning.

Hardware Requirements

Table 4.1 shows the bill of quantities for the implementation of the client device. The various quantities of components for prototyping are stated. It should be noted that the remote site components (servers, routers/gateways, mast, etc) are not captured since thinkspeak cloud server is used for this prototyping however, a production environment would require server and network installations in appropriate location along the highway.

Table 4.1: Bill of quantities

Components	**Quantity**
ESP8266-development board	1
SIM800L GSM	1
GPS-uBlox Neo 6M	1
16×2 I2C LCD	1
Buzzer	1
Server-grade PC (HP intel (R) Celeron (R) CPU 3050, 1.6Ghz PC @ 2GB RAM)	1
USB cables	1
1K Ohm resistors, 4.4k Ohm resistors	6
Breadboard	1
Micro USB cable for connecting ESP8266 NodeMCU to PC	1
Jumper wires	30

The ESP8266- 12E Wi-Fi Development Board

The ESP8266 Wi-Fi Module is a silicon on chip (SoC) provides access to a Wi-Fi network. Each ESP8266 module comes with already programmed AT command set firmware, that is, it can hook up to Arduino device and gain access to Wi-Fi features. The ESP8266 module is cost-effective and has a huge, and continuous growing, community. It is also an independent SOC with incorporated TCP/IP convention stack that can give any micro-controller access to your Wi-Fi arrangement. The ESP8266 is able to do either facilitating an application or offloading all Wi-Fi features from another application processor. Fig. 4.1 shows the pin configuration of the ESP8266-12 Wifi development board. The micro USB cable from the Laptop was inserted into the micro USB port of the Node MCU in order to supply a 5Volts to the node MCU. The VU pin delivered

ISSN No. 2454-6194 | DOI: 10.51584/IJRIAS |Volume IX Issue X October 2024

voltage of 5V, the G terminals had voltages of 0V ground while the 3V terminals delivered output voltages of 3V each. The D0, D1, D2, D3, D4, D5, D6, D7, and D8 Pins were all used for interfacing the Node MCU to the various modules used for the set up.

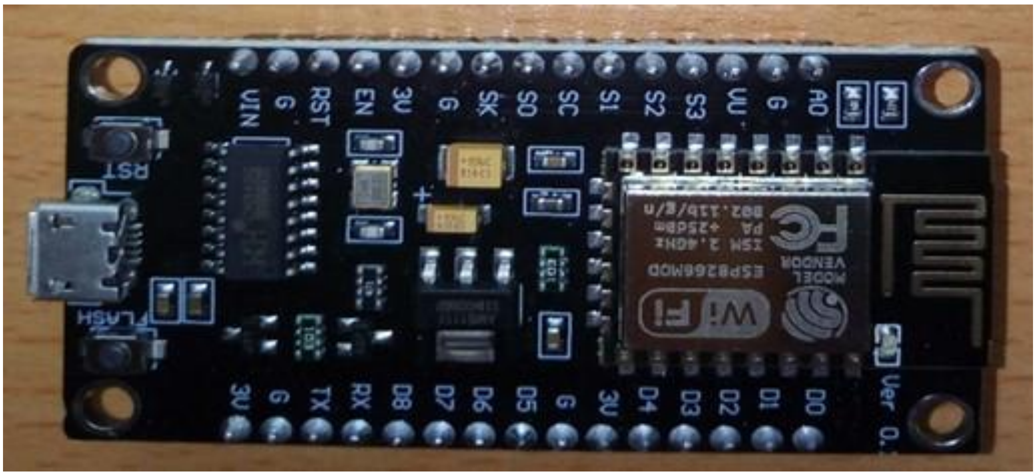


Fig. 4.1 ESP8266- 12E Wi-Fi development board

The SIM800L GSM

Fig. 4.2 shows the pin configuration of SIM800L GSM. As shown in Fig. 4.2, the following pins are clearly marked on this module: RING, DTR, MICP, MICN, SPKP, SPKN, NET, VCC, RESET, RXD, TXD and GND.

Fig. 4.2 SIM800L GSM

In order to interface SIM800L to NodeMCU, the RXD pin of SIM800L was connected to D5 pin of node MCU, TXD pin of SIM800L was connected to D6 pin of Node MCU, and the GND pin was connected to the G pin of the Node MCU. Finally, the biasing voltage of 4V, VCC of the SIM800L was tapped from VU by means of a voltage divider circuit.

The formular for the voltage divider circuit was:

$$V_{out} = V_{in} \text{ x } \frac{R6}{R5+R6} \quad \text{……………………………………………….. (3)}$$

where:

Vout = 4V (desired)

Vin = 5V (Available at VU pin of Node MCU)

ISSN No. 2454-6194 | DOI: 10.51584/IJRIAS |Volume IX Issue X October 2024

R5 = 1KΩ was assumed and calculation was done for R6 which gave 4.2KΩ approximately 4.4KΩ

Therefore, using R5=1KΩ and R6=4.4KΩ the voltage of 5V from pin VU of Node MCU was divided to get 4V at the center as shown in Fig. 4.9. This 4V was the biasing voltage of the SIM800L.

The Ublox Neo 6M GPS (Global Positioning System):

Fig. 4.3 below shows the Ublox Neo 6M GPS used in this study. The Pinout of GPS module are VCC, GND, RX, and TX. The RX pin of the GPS module was connected to D3 pin of the Node MCU, TX pin of the GPS module was connected to D4 pin of the Node MCU, GND pin of the GPS module was connected to G pin of the Node MCU and finally, the VCC pin of the GPS module was connected to one of the 3V pin of the Node MCU via a 1kΩ resistor, R4.

Fig. 4.3 Ublox Neo 6M GPS

The 16×2 I2C LCD

Four (4) pins of the LCD were used in this study and they are GND, VCC, SCL, SDA as shown in fig. 4.4. These pins were connected appropriately to the ESP8266 module. The SCL pin of the LCD was connected to D1 of the Node MCU, SDA pin of the LCD was connected to D2 of the Node MCU, the GND pin of the LCD module was connected to G pin of the Node MCU and finally, the VCC pin of the LCD module was connected to the VU pin = 5V of the Node MCU via a 1kΩ resistor, R1.

Fig. 4.4: 16×2 I2C LCD

The Buzzer

Fig. 4.5 shows a Piezo buzzer used for this study. A Piezo buzzer is a device that is used to generate beep sound (generally a warning or alert in embedded system). It is a two terminal device. The positive terminal has a red coded wire while the negative terminal has a black coded wire. In order for the buzzer to be interfaced with the Node MCU, the positive terminal of the buzzer was connected to pin D0 of Node MCU while the negative terminal of the buzzer was connected to G pin of the Node MCU.

INTERNATIONAL JOURNAL OF RESEARCH AND INNOVATION IN APPLIED SCIENCE (IJRIAS)
ISSN No. 2454-6194 | DOI: 10.51584/IJRIAS |Volume IX Issue X October 2024

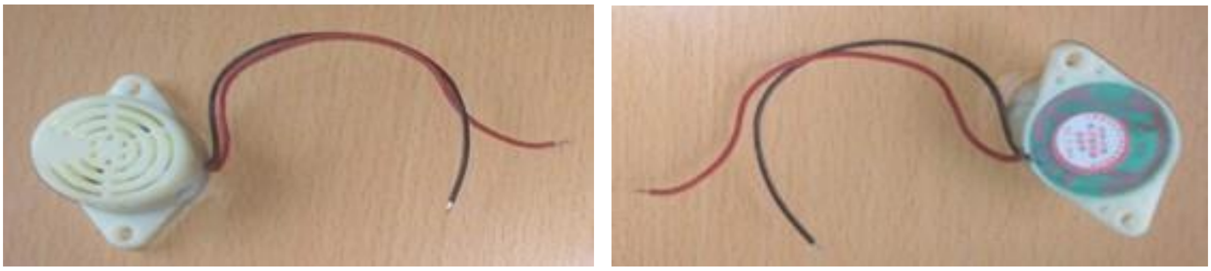


Fig. 4.5: Buzzer

The Jumper Wires

Fig. 4.6 shows the Jumper Wires used in the set up. Jumper wires are insulated tiny conductors used for joining points on bread board or points from modules to bread board or modules to modules. Three types of jumpers were used. In connecting a pin terminal module or device to the bread board, a female to male jumper was used. In connecting a pin terminal module or device to another pin terminal module, a female to female jumper was used. Finally in connecting a point on the breadboard to another point on the bread board, a male to male jumper was used. The female side of a jumper is any side that has a hole that can accommodate a pin while the male side of a jumper is any side that has a pin that can be inserted into a hole.

Fig. 4.6: Jumper wires

The Breadboard

Breadboards are work boards for temporary electronic circuits. It is used to make quick electrical connections between electrical components for prototyping and testing circuits before they are soldered permanently. Breadboards have many small sockets on them, and some groups of sockets are electrically connected to each other. On the underside of the board there are many small metal strips which connect groups of sockets together and allow electricity to flow freely between them.

In this study, two breadboards were technically glued together for the purpose of accommodating the various components.

Fig. 4.7: A single breadboard

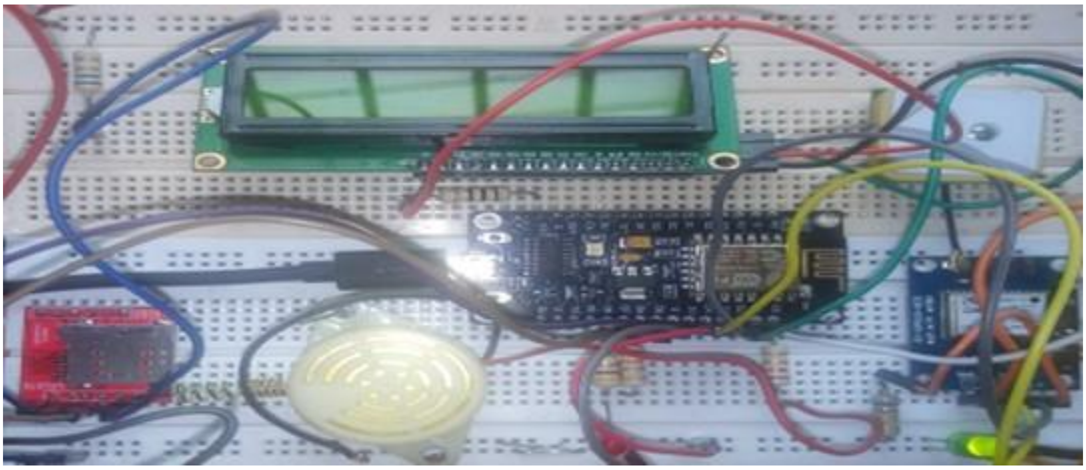


Fig. 4.8: Two glued breadboard

Circuit Diagram of the Proposed System

Fig. 4.9 below is the circuit diagram for the interfacing of the various components to the Node MCU.

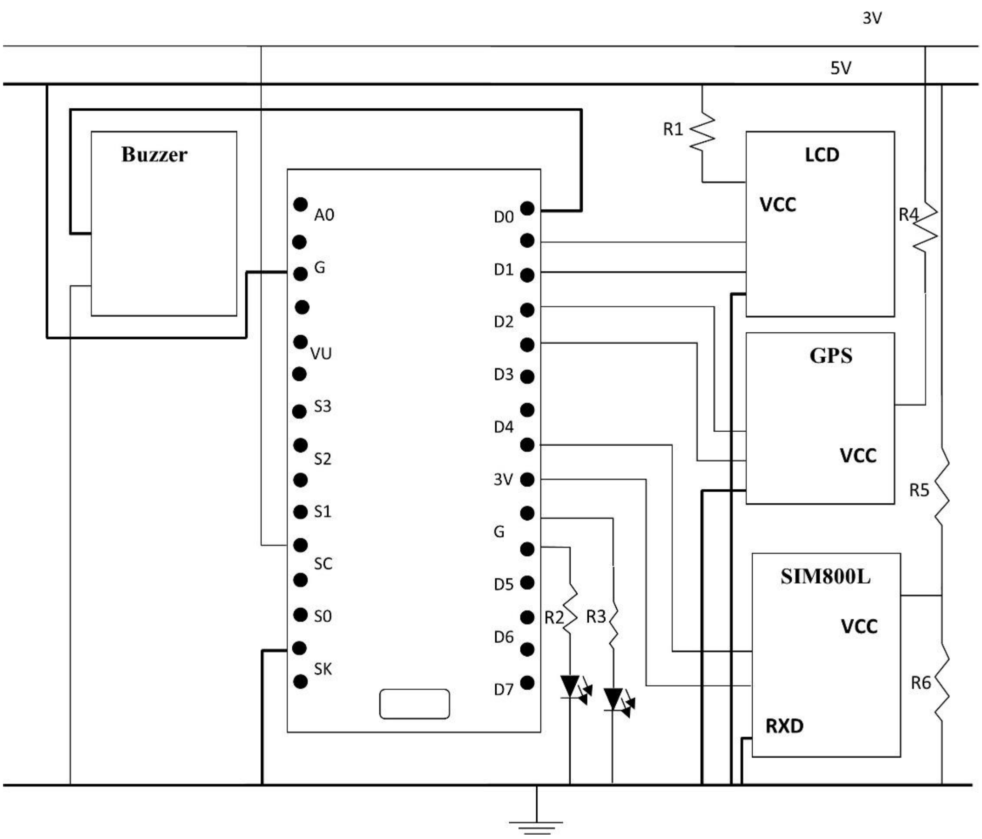


Fig. 4.9: Circuit diagram of the proposed system

Circuit Configuration

Fig. 4.10 below shows the complete setup of the device. The 16x12 12C LCD, GPS module, SIM800L GSM module, and the buzzer were all interfaced with the ESP8266-12E Node MCU. The GPS module was used to monitor the real-time location of the vehicle from anywhere and was displayed by the LCD while the SIM800L was used for sending and receiving text messages and calls.. After successful completion of hardware as per the above circuit diagram, now its time to set up the IoT platform, where the GPS coordinates are stored. We used ThingSpeak to store the latitude and longitude data on the cloud and graphically visualize the GPS data. Again ThingSpeak IoT cloud was also used to store the history of accident prone locations and associated data from Bayesian learning

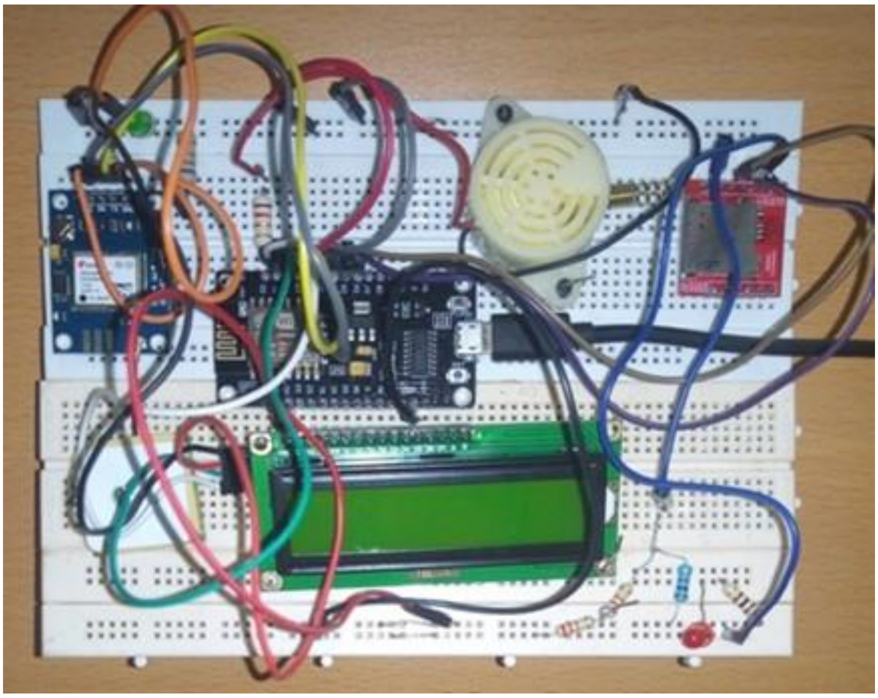


Fig. 4.10 Circuit implementation

Implementation of the Software Component

Arduino IDE

The Arduino Integrated Development Environment - or Arduino Software (IDE) - contains a text editor for writing code, a message area, a text console, a toolbar with buttons for common functions and a series of menus. It connects to the Arduino and Genuino hardware to upload programs and communicate with them. The Arduino Integrated Development Environment (IDE) is the main text editing program used for Arduino programming. Essentially, the IDE translates and compiles your sketches into code that Arduino can understand. Once the Arduino code is compiled it is then uploaded to the board's memory.

The Arduino board is connected to a computer via USB, where it connects with the Arduino integrated development environment (IDE). The user writes the Arduino code in the IDE, and then uploads it to the microcontroller which executes the code, interacting with inputs and outputs such as sensors, motors, and lights.

ThingSpeak Account Creation

After successful connection of the hardware shown in Fig. 4.10 above, it was time to set up the IoT platform, where the GPS coordinates are stored. We used ThingSpeak to store the latitude and longitude data on the cloud and graphically visualize the GPS data.

First, go to https://thingspeak.com/ and create a free Mathworks account. Next, Sign in to ThingSpeak using the credentials and click on “New Channel”. Fill up the details of the project like Name, Field names, etc. Here we have to create two field names such as Latitude and Longitude. Then click on “Save channel”.

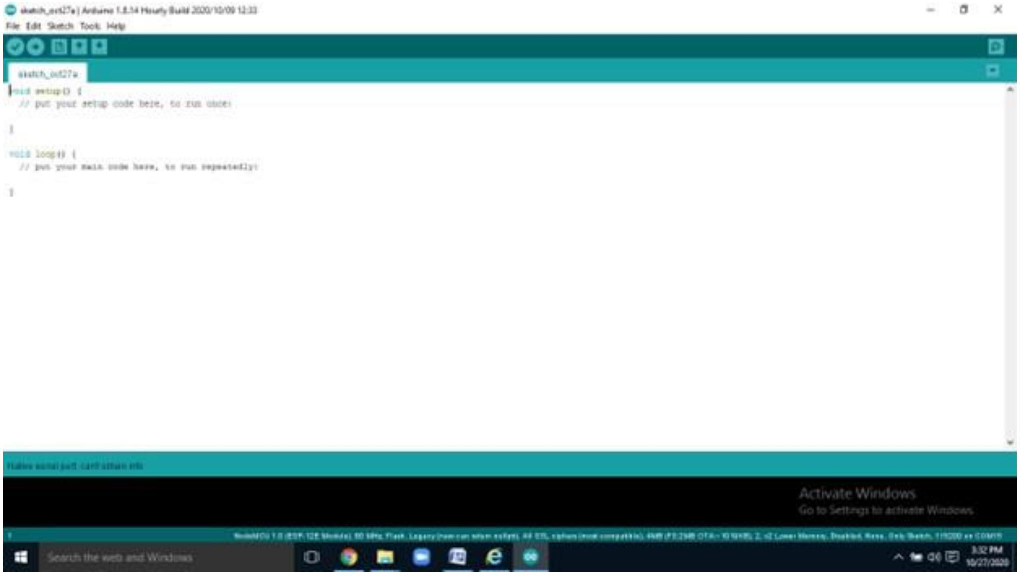
The third step was to Select the created channel and record the Channel ID, which is at the top of the channel view and the API key, which can be found on the API Keys tab of the channel view.

Programming Nodemcu for Accident Mitigation System

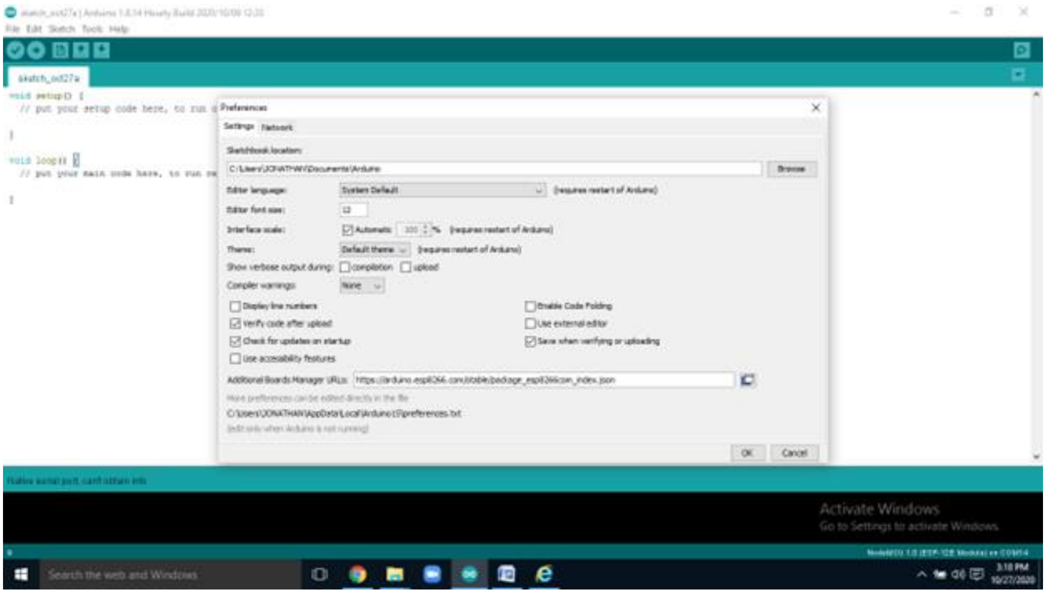
After the successful completion of the Hardware connections and ThingSpeak setup, now it’s time to program the ESP8266 NodeMCU. To upload code into NodeMCU using Arduino IDE, the following steps were followed:

1. Open Arduino IDE, then go to File–>Preferences–>Settings.

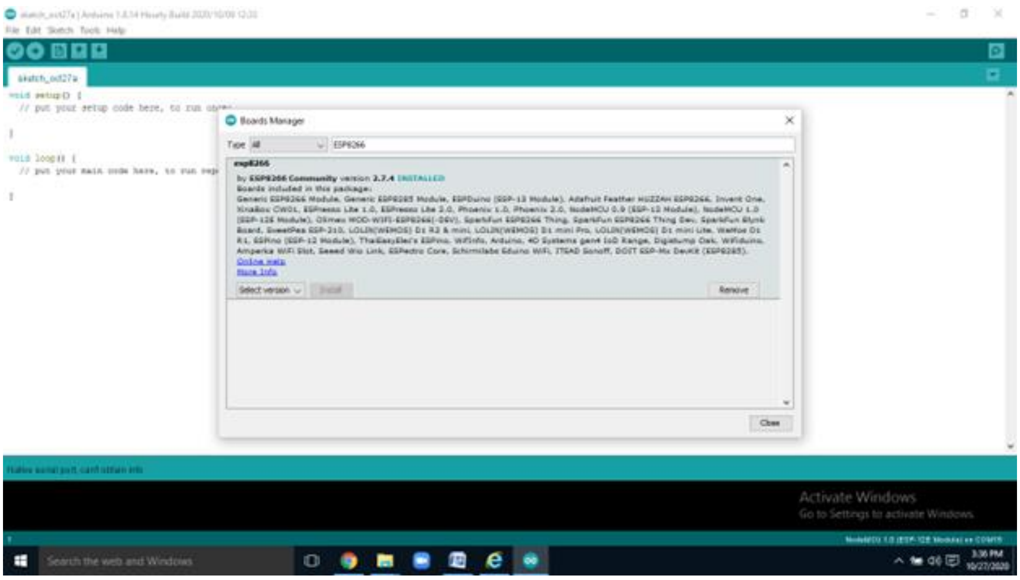
INTERNATIONAL JOURNAL OF RESEARCH AND INNOVATION IN APPLIED SCIENCE (IJRIAS)
ISSN No. 2454-6194 | DOI: 10.51584/IJRIAS |Volume IX Issue X October 2024



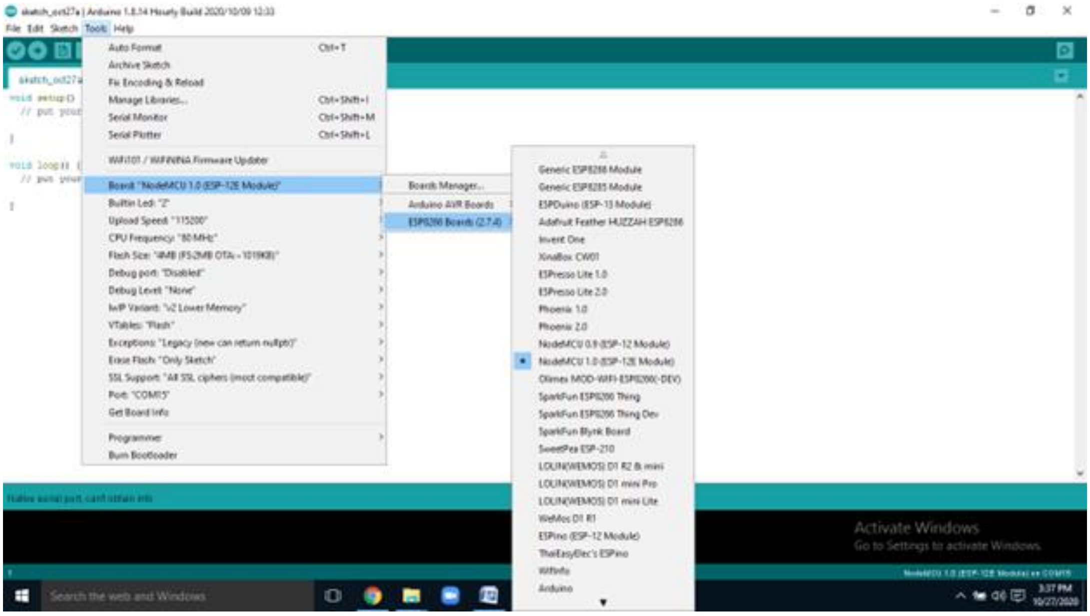
2. Type https://arduino.esp8266.com/stable/package_esp8266com_index.json in the ‘Additional Board Manager URL’ field and click ‘Ok’.



3. Now go to Tools > Board > Boards Manager. In the Boards Manager window, Type ESP8266 in the search box, select the latest version of the board and click on install.



4. After installation is complete, go to Tools ->Board -> and select NodeMCU 1.0(ESP-12E Module). Now you can program NodeMCU with Arduino IDE.



5. After setting up NodeMCU in Arduino IDE, the code was uploaded into NodeMCU.

Testing of IoT-Driven Accident Mitigation System

After connecting the hardware and uploading the code, the circuit was powered on. Visible on the LCD are some notifications messages. Now the web browser was opened and the IP address of the NodeMCU was typed in. There would be a link that would take one to the google map with the current location of the vehicle. The IP address of NodeMCU is displayed on LCD after Wi-Fi is connected successfully. At the same time ThingSpeak would also log the Latitude and Longitude of the vehicle.

RESULTS

This study evaluated the performance of a Bayesian learning framework integrated with an IoT network to enhance highway safety on a selected segment of the Benin-Onitsha Expressway. Data were collected over a six-month period from 50 deployed sensor nodes, encompassing GPS coordinates, timestamps, vehicle speed, and weather conditions. Accident reports from official sources served as the ground truth for evaluating the system's predictive capabilities.

Accident Prediction Performance

The Bayesian model demonstrated a strong ability to identify accident-prone locations. The area under the receiver operating Characteristic curve (AUC-ROC) for accident prediction was 0.82, indicating excellent discrimination between high-risk and low-risk areas. At an optimized threshold, the model achieved 75% precision and 80% recall, signifying a balance between minimizing false positives and maximizing the identification of true positive accident-prone locations. While the false positive rate was 15%, this was deemed acceptable considering the significant reduction in accidents observed (detailed below). Further analysis of the false positives revealed that the majority stemmed from temporary congestion rather than actual accidents, providing valuable insights for future system refinements.

Impact on Accident Reduction

A comparative analysis of accident statistics for the monitored expressway segment before and after system deployment revealed a statistically significant reduction in accidents. The number of reported accidents decreased from 25 in the six months preceding deployment to 15 in the six months following deployment ($\chi^2 = 3.75$, df = 1, $p < 0.05$). While this reduction strongly suggests a positive impact of the system, further investigation is warranted to definitively establish causality and rule out the influence of confounding factors such as seasonal variations in traffic patterns or concurrent road maintenance initiatives.

System Reliability and Scalability

The IoT network exhibited high reliability, maintaining an average uptime of 98%. Data transmission was robust, with minimal data loss (<2%). The Bayesian model demonstrated adaptability, effectively updating its predictions as new data became available. Challenges were encountered with GPS signal interference in heavily forested areas, resulting in temporary data gaps. Mitigation strategies, including the deployment of additional sensors with alternative positioning systems, are being explored to enhance the system's robustness and expand its coverage.

Limitations

The study had several limitations:

1. The sample size of the monitored expressway segment was relatively small.
2. The accuracy of accident reports from official sources may vary.
3. The study did not explicitly control for other factors that might influence accident rates, such as changes in traffic volume or road maintenance.

CONCLUSION

An implementation of a low cost, reliable, reusable and easily maintainable system, focusing on the mitigation of accident on highways has been done. This is an efficient IoT-Driven Bayesian Learning system, which can provide timely alerts to driver and travelers whenever there is a risk of an accident. The risk in this sense is based on road accident history stored in the cloud and brought about by Bayesian Learning. The experimental results show that it works with real-time data from the environment which is processed by Bayesian Learning efficiently. One of the most useful traits of Bayesian Learning is that it can work with low cost processing units (in our case, Node MCU). Our proposed system predicts and determines the system behavior by considering the threshold value for the real-time captured dataset. As a result, the system performs well. The results show that the integration of IoT and Bayesian Learning yields detection and mitigation of car accidents in real time traffic. The proposed system fulfills most of the necessities of a smart system with minimal effort and maximum gain. Our proposed system works in an efficient manner on roads with a 4G/high speed internet connection. Moreover, the location provided by the GPS module used in this system helps in providing prompt email alerts. The motivation behind designing this system is the desire to reduce accidents on highways and reach increased system performance overall.

REFERENCES

1. Alnashwan, Raghad & Saad, Areej & Qudaih, Hala & Albraheem, Lamya & Mashaabi, Malak. (2023). IoT Based Accident Prevention System Using Machine Learning Techniques. [Preprint]. ResearchGate. https://www.researchgate.net/publication/369595854
2. Ammar, M., Giovanni R., & Bruno Crispo, (2018). "Internet of Things: A survey on the security of IoT frameworks" *Journal of Information Security and Applications 38 (2018):* 8-27.
3. Babitha, D., Mohammed, I., Subrata, C., Ramya, G., Kolla, B. P., (2020). *International Journal of Advanced Trends in Computer Science and Engineering* https://doi.org/10.30534/ijatcse/2020/132922020
4. Bagga, P., Das, A. K., Wazid, M., Rodrigues, J. J., Choo, K.-K. R., & Park, Y. (2021). On the design of mutual authentication and key agreement protocol in Internet of Vehicles-enabled intelligent transportation system. IEEE Transactions on Vehicular Technology, 70(2), 1736-1751. https://doi.org/10.1109/TVT.2021.3050614
5. Bargahi, M., Barati, H., & Yazici, A. (2023). Relationship between criticality and travel time reliability in transportation networks. In 2023 IEEE 26th International Conference on Intelligent Transportation Systems (ITSC) (pp. 2479-2484). IEEE. https://doi.org/10.1109/ITSC57777.2023.10421885

6. Belgaum, M. R., Soomro, S., Alansari, Z., Musa, S., Alam, M., & Su'ud, M. M. (2017). Challenges: Bridge between cloud and IoT. In Engineering Technologies and Applied Sciences (ICETAS), 2017 *4th IEEE International Conference on* (1-5). IEEE.
7. Coffin, D., Oliver, S., & VerWey, J., (2019) Building Vehicle Autonomy: Sensors, Semiconductors, Software and U.S. *Competitiveness* (November 2019). Office of Industries Working Paper ID-063, November 2019, Available at SSRN: https://ssrn.com/abstract=3492778 or http://dx.doi.org/10.2139/ssrn.3492778
8. Cui, Y., & Lei, D. (2023). Design of highway intelligent transportation system based on the Internet of Things and artificial intelligence. IEEE Access. https://doi.org/10.1109/ACCESS.2023.1234567
9. Das T., Sinmon B., & Char L. (2017). "Vehicle accident prevent cum location and monitoring system", 2017. *8th Annual Industrial Automation and Electromechanical Engineering Conference (IEMECON)*, August 2017
10. Devarajan, G. G., Kumaran, U., Chandran, G., Mahapatra, R. P., & Alkhayyat, A. (2024). Next generation imaging methodology: An intelligent transportation system for consumer industry. IEEE Transactions on Consumer Electronics. https://doi.org/10.1109/TCE.2024.1234567
11. Dhingra, S., Madda, R. B., Patan, R., Jiao, P., Barri, K., & Alavi, A. H. (2021). Internet of things-based fog and cloud computing technology for smart traffic monitoring. *Internet of Things*, 14, 100175. https://doi.org/10.1016/j.iot.2021.100175
12. Faheem A. M. (2017). Road Accidents and Prevention. *International Journal of Engineering Development and Research, 5(2).* www.ijedr.org
13. Fan, Z. Y., Liu, C., Cai, D. J., & Yue, S. (2019) Research on black spot identification of safety in urban traffic accidents based on machine learning method. *Saf. Sci. 2019, 118, 607–616.*
14. Francois-Lavet, V., Henderson, P., Islam, R., Bellemare, M. G., & Pineau, J. (2018). An introduction to deep reinforcement learning. *Foundations and Trends® in Machine Learning, 11(3–4), 219–354.*
15. George, Y., Athanasios T., & George, P. (2017). Investigation of road accident severity per vehicle type. *Transportation Research Procedia. World Conference on Transport Research-WCTR 2016. Shanghai. 25:2076–2083.* Available from: http://dx.doi.org/10.1016/j.trpro. 2017.05.401
16. Gohar, A., & Nencioni, G. (2021). The role of 5G technologies in a smart city: The case for intelligent transportation system. *Sustainability*, 13(9), 5188. https://doi.org/10.3390/su13095188
17. Goniewicz, K., Goniewicz, M., Pawłowski, W., & Fiedor, P. (2015). Road accident rates: strategies and programmes for improving road traffic safety. *European Journal of Trauma and Emergency Surgery. https://DOI 10.1007/s00068-015-0544-6*
18. Gopalan, S. H., Vignesh, V., Rajkumar, D. U. S., Velmurugan, A., Deepa, D., & Dhanapal, R. (2024). Fuzzified swarm intelligence framework using FPSOR algorithm for high-speed MANET-Internet of Things (IoT). Measurement: Sensors, 31, 101000. https://doi.org/10.1016/j.measen.2024.101000
19. Hamid, K., Bahman, J., Mahdi, J., and Reza, N. J. (2020). Artificial Intelligence and Internet of Things for Autonomous Vehicles. https://www.researchgate.net/publication/335021813 DOI: 10.1007/978-3-030-18963-1_2
20. Harum, K. (2016). "Vehicle Detection and Tracking System IoT based". *International Research Journal of Engineering and Technology (IRJET),Volume-5,Issue-8.*
21. Hossain, M. Y., & George, F. P., (2018). "IOT Based Real-Time Drowsy Driving Detection System for the Prevention of Road Accidents." *International Conference on Intelligent Informatics and Biomedical Sciences (ICIIBMS), Bangkok, 20(18), 190-195*.
22. Imteaj, B., (2015) "Smart Vehicle Accident Detection and Alarming System Using a Smartphone", conference: 2015 *International Conference on Computer and Information Engineering (ICCIE)*, November 2015
23. Javadi, B., Calheiros, R. N., Matawie, K. M., Ginige, A., & Cook, A. (2018). Smart nutrition monitoring system using heterogeneous internet of things platform. In G. Fortino, A. B. M. S. Ali, M. Pathan, A. Guerrieri, G. & Fatta D. (Eds.), Internet and distributed computing systems (pp. 63–74). Fiji: Springer.
24. Kaur, B., Singh, S., Kumar, A., & Gupta, R. (2023). Internet of things (IoT) security dataset evolution: Challenges and future directions. Internet of Things, 100780. https://doi.org/10.1016/j.iot.2023.100780
25. Kheder, M. Q., & Mohammed, A. A. (2022). IoT-based vision techniques in autonomous driving: A review. ADCAIJ: Advances in Distributed Computing and Artificial Intelligence Journal, 11(3), 367-394. https://doi.org/10.14201/adcaij.28821

26. Kong, W., Lin, W., Babiloni, F., Hu, S., & Borghini, G. (2015) Investigating driver fatigue versus alertness using the granger causality network. *Sensors 2015(15) 19181–19198.* doi: 10.3390/s150819181.
27. Kusy, M., & Zajdel, R. (2015). Application of reinforcement learning algorithms for the adaptive computation of the smoothing parameter for probabilistic neural network. *IEEE Transactions on Neural Networks and Learning Systems*, 26, 2163–2175.
28. Liu, C., & Ke, L. (2023). Cloud assisted Internet of things intelligent transportation system and the traffic control system in the smart city. Journal of Control and Decision, 10(2), 174-187. https://doi.org/10.1080/15716854.2023.1234567
29. Liu, W. (2023). IoT-based multi-channel information integration method for wireless sensor networks. *Proceedings of the Indian National Science Academy*, 89(3), 705-714. https://doi.org/10.1007/s43539-023-00234-5
30. Liu, W. (2023). QoS-aware resource allocation method for the Internet of Things using triplet and heterogeneous earliest finish time algorithms. *Proceedings of the Indian National Science Academy*, 89(3), 1-9. https://doi.org/10.1007/s43539-023-00200-5
31. Liyanage, T. D., Rengarasu, T. M. (2015). Traffic Accident Analysis and Development of Accident Prediction Model. In: Annual Session of IESL. *The Institute of Engineers*. Sri Lanka; 2015. p. 105–9.
32. Lu, C., & Wang, F. (2024). Towards secure Internet of Things-enabled intelligent transportation systems: A comprehensive review. International Journal of Advanced Computer Science and Applications, 15(7), 82. https://www.ijacsa.thesai.org
33. Lv, Z., & Shang, W. (2023). Impacts of intelligent transportation systems on energy conservation and emission reduction of transport systems: A comprehensive review. Green Technologies and Sustainability, 1(1), 100002. https://doi.org/10.1016/j.gtsus.2023.100002
34. Mahdavinejad, K., & Mohammad, S. (2018). "Machine learning for Internet of Things data analysis: A survey." Digital Communications and Networks, 4.3 (2018), 161-175..
35. Maria, C. A. A., (2020). Integrating Spatial Data Analysis for Road Traffic Incident Response System. *International Journal of Advanced Trends in Computer Science and Engineering, 9(1.2).* https://doi.org/10.30534/ijatcse/2020/3291.22020
36. Maria, C.A.A, Rosemarie, T. B., Jocelyn, O. T., Daniel, E. M., Jr., (2020). Analysis and System Architecture Design for Road Traffic Incidents. *International Journal of Advanced Trends in Computer Science and Engineering*, *9(12)* https://doi.org/10.30534/ijatcse/2020/3391.22020
37. Maria, T. V., Eric, M., Riyanto, J., & Tuga M. (2020) Heart Disease Prediction System using Data Mining Classification Techniques: Naïve Bayes, KNN, and Decision Tree. *International Journal of Advanced Trends in Computer Science and Engineering 9(3)* https://doi.org/10.30534/ijatcse/2020/82932020
38. Millicent, N. U., Ambrose, A. A., Aderonke, A. O., Hilary, I. O., Olanike, S. N. & Felix, C. (2020). Blockchain Framework for Securing E-Learning System. *International Journal of Advanced Trends in Computer Science and Engineering*, 9(3). https://doi.org/10.30534/ijatcse/2020/68932020
39. Mohanta, B. K., Jena, D., Mohapatra, N., Ramasubbareddy, S., & Rawal, B. S. (2022). Machine learning based accident prediction in secure IoT enable transportation system. Journal of Intelligent & Fuzzy Systems, 42(2), 713-725. https://doi.org/10.3233/JIFS-189743
40. Mohseni, M., Amirghafouri, F., & Pourghebleh, B. (2022). CEDAR: A cluster-based energy-aware data aggregation routing protocol in the Internet of Things using capuchin search algorithm and fuzzy logic. Peer-to-Peer Networking and Applications, 1-21. https://doi.org/10.1007/s12083-022-00638-1
41. Muthusamy, A. P., Rajendran, M., Ramesh, K., & Sivaprakash, P. (2015). A Review on Road Traffic Accident and Related Factors. *International Journal of Applied Engineering Research, 10(11),* 28177-28183 http://www.ripublication.com
42. Nak, M. S. & Mauricio, R. (2015). World Bank Blog. https://blogs.worldbank.org/ transport/road-crashes-have-more-impact-poverty-you-probably-thought (accessed 20th August, 2020)
43. Nanda, S., Joshi, H., and Khairnar, S. (2018) "An IOT Based Smart System for Accident Prevention and Detection." *Fourth International Conference on Computing Communication Control and Automation (ICCUBEA), Pune, India, 2018, 1-6.*
44. Navod, F., & Bindu Tushara, D. (2018) "Vehicle Monitoring, controlling and tracking System by using android application". *International Journal of Technical Research and Applications, 4(1)*
45. Niu, Y., Fan, Y., & Ju, X. (2024). Critical review on data-driven approaches for learning from accidents:

Comparative analysis and future research. Safety Science, 171, 106381. https://doi.org/10.1016/j.ssci.2023.106381

46. Nwankwo, W., Olayinka, A. S., Ukhurebor, & Kingsley, E. (2019). The urban traffic congestion problem in Benin City and the search for an ICT-improved solution. *International journal of scientific & technology research* 8(12), December 2019 ISSN 2277-8616 65 IJSTR©2019 www.ijstr.org
47. Nwankwo, Wilson & Adetunji, Charles & Akinola, Olayinka & Odunze, Daisy. (2022). IoT-Driven Bayesian Learning: A Case Study of Reducing Road Accidents of Commercial Vehicles on Highways. 10.1007/978-3-030-87059-1_15.
48. Oluwaseyi, J. A., & Gbadamosi, K. T. (2017). Road traffic crashes in Nigeria: causes and consequences. *Transport & Logistics: The International Journal*, 17(42). ISSN 2406-1069
49. Pathik, N., Gupta, R. K., Sahu, Y., Sharma, A., Masud, M., & Baz, M. (2022). AI enabled accident detection and alert system using IoT and deep learning for smart cities. Sustainability, 14(13), 7701. https://doi.org/10.3390/su14137701
50. Pourghebleh, B., Hekmati, N., Davoudnia, Z., & Sadeghi, M. (2022). A roadmap towards energy-efficient data fusion methods in the Internet of Things. Concurrency and Computation: Practice and Experience, 34(18), e6959. https://doi.org/10.1002/cpe.6959
51. Quy, V. K., Nam, V. H., Linh, D. M., & Ngoc, L. A. (2022). Routing algorithms for MANET-IoT networks: A comprehensive survey. Wireless Personal Communications, 125(4), 3501-3525. https://doi.org/10.1007/s11277-022-09080-9
52. Ruchin, J. (2018) "A Congestion Control System Based on VANET for Small Length Roads", *Annals of Emerging Technologies in Computing (AETiC)*, Published by International Association of Educators and Researchers (IAER), 2(1), pp. 17-21. Available: http://aetic. theiaer.org/archive/v2n1/p3.pdf
53. Sai, K. K. V. V. N. L., Kamakshi, D. R. N., Pavan, K. N., Mukundini, K., & Karthi, R. (2020). Building an Intrusion Detection System for IoT Environment using Machine Learning techniques. *Third International Conference on Computing and Network Communications (CoCoNet'19).* http://creativecommons.org/licenses/by-nc-nd/4.0/
54. Sarasvathi, N., & Fong, J., & Zu, X. (2018) "Study and Implementation of Internet of Things (IoT) Based Vehicle Safety Alert and Tracking System" - *INTI Journal, 1 (10). 1-11. ISSN e2600-7920.*
55. Sohail, A., Cheema, M. A., Ali, M. E., Toosi, A. N., & Rakha, H. A. (2023). Data-driven approaches for road safety: A comprehensive systematic literature review. Safety Science, 105949. https://doi.org/10.1016/j.ssci.2022.105949
56. Soori, M., Arezoo, B., & Dastres, R. (2023). Internet of things for smart factories in Industry 4.0: A review. Internet of Things and Cyber-Physical Systems. https://doi.org/10.1016/j.iotcps.2023.04.006
57. Syafrudin, M., Alfian, G., Fitriyani, N., & Rhee, J. (2018) Performance analysis of IoT-Based sensor, big data processing, and machine learning model for real-time monitoring system in automotive manufacturing. *Sensors 2018,18(2946).*
58. Truong, T. T. (2020) Predicting and Preventing Transport Accidents with Fuzzy Relationships. *International Journal of Advanced Trends in Computer Science and Engineering, 9(2).* https://doi.org/10.30534/ijatcse/2020/89922020
59. Vempaty P. & Kanakala S., (2020). Plant Disease Detection Using Convolutional Neural Networks. *International Journal of Advanced Trends in Computer Science and Engineering, 9(3)* https://doi.org/10.30534/ijatcse/2020/21932020
60. Verma, S., Zeadally, S., Kaur, S., & Sharma, A. K. (2021). Intelligent and secure clustering in wireless sensor network (WSN)-based intelligent transportation systems. *IEEE Transactions on Intelligent Transportation Systems*, 23(8), 13473-13481. https://doi.org/10.1109/TITS.2021.3061234
61. Victor, A., Kayode, A., & Abimbola, A. (2015). Automatic and real-time Pothole detection and Traffic monitoring system using Smartphone Technology. https://www.researchgate. net/publication/28162839 (accessed 21st August, 2020)
62. Wadhahi, N. T. S. A., Hussain, S. M., Yosof, K. M., Hussain S. A., & Singh, A. V. (2018) "Accidents Detection and Prevention System to reduce Traffic Hazards using IR Sensors." *2018 7th International Conference on Reliability, Infocom Technologies and Optimization (Trends and Future Directions) (ICRITO), Noida, India, 2018, pp. 737-741.*
63. Wang, F.-Y., Zhang, Y., Liu, J., & Chen, X. (2023). Transportation 5.0: The DAO to safe, secure, and sustainable intelligent transportation systems. IEEE Transactions on Intelligent Transportation Systems.

https://doi.org/10.1109/TITS.2023.1234567

64. Wang, Z., Yue Y., Li Q., Nie K., Tu W., & Liang S. (2017). Analyzing risk factors for fatality in urban traffic crashes: A case study of Wuhan, China. *Sustainability*, 9(6):1–13.
65. Whig, P., Velu, A., Nadikattu, R. R., & Alkali, Y. J. (2024). Role of AI and IoT in intelligent transportation. In Artificial Intelligence for Future Intelligent Transportation (pp. 199-220). Apple Academic Press.
66. World Bank (2018). Road Deaths and Injuries Hold Back Economic Growth in Developing Countries. 2018. Available from: https://www.worldbank.org/en/news/press-release/2018/01/09/road-deaths-andinjuries-hold-back-economic-growth-in-developing-countries
67. World Health Organization (2020). Global status report on road safety 2020. 2020;1–16. https://www.who.int/news-room/fact-sheets/detail/road-traffic-injuries
68. Xiao, Z., Wang, Y., Zhang, H., & Liu, Y. (2023). Tensor and confident information coverage based reliability evaluation for large-scale intelligent transportation wireless sensor networks. IEEE Transactions on Vehicular Technology. https://doi.org/10.1109/TVT.2023.1234567
69. Xue, H., Zhang, Z., & Zhang, Y. (2023). A novel cluster-based routing protocol for WSN-enabled IoT using water-cycle algorithm. Proceedings of the Indian National Science Academy, 89(3), 724-730. https://doi.org/10.1007/s43538-023-00184-8
70. Yuvaraj, N., Praghash, K., Raja, R. A., & Karthikeyan, T. (2022). An investigation of garbage disposal electric vehicles (GDEVs) integrated with deep neural networking (DNN) and intelligent transportation system (ITS) in smart city management system (SCMS). Wireless Personal Communications, 123(2), 1733-1752. https://doi.org/10.1007/s11277-022-09045-5
71. Zuo, K., Wang, Y., Zhang, Y., & Liu, J. (2024). Security enhanced privacy-preserving data aggregation scheme for intelligent transportation system. The Journal of Supercomputing, 80(1), 1-28.