TRIBHUVAN UNIVERSITY

INSTITUTE OF ENGINEERING

THAPATHALI CAMPUS

A MINOR PROJECT PROPOSAL

ON

EDR-BASED INTELLIGENT VEHICLE ACCIDENT PREDICTION WITH MULTISENSOR FUSION AND EDGE SUMMARIZATION

Submitted By:

Prenisha Upreti	(THA079BEI029)
Roshan Kr. Gupta	(THA079BEI034)
Suman Phuyal	(THA079BEI042)
Yugal Nyoupane	(THA079BEI048)

Submitted To:

Department of Electronics and Computer Engineering

Thapathali Campus

Kathmandu, Nepal

Under the Supervision of

Er. Umesh Kanta Ghimire (UKG Sir)

December 2025

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We would like to thank the Institute of Engineering, Tribhuvan University for providing us the opportunity to implement our knowledge and experience and showcase it into a project this semester.

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We would also like to thank your supervisor; **Umesh Kanta Ghimire** for guiding, motivating and listening to the thoughts and creativity that run through our brains.

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ABSTRACT

"EDR(EventDataRecorder)BasedIntelligent Vehicle Accident Prediction with Multisensor Fusion and Edge Summarization" highlights the prevention mechanism and alert mechanism in the case of an accident. According to WHO "Approximately 1.19 million people die each year as a result of road traffic crashes." The casualties on the road are often misunderstood and blamed on drivers but the causes are often different. The real cause is never known. The miscommunication and misinformation of vehicle status, in pre-event and post-event of accident often lead into bad accident prevention. This project focuses primarily on prevention and post-event accident event data recorder and alerting via SOS in case of an accident. Multiple sensors like Flame Sensor, Gyroscope, GPS, Crash sensors are connected and embedded with a MultiSensor Fusion algorithm which gives accurate and comprehensive inferences than using some individual sensors with complex algorithms. In a microcontroller, by using the Multifusion algorithm, we integrate a waterfall model for the analytical viewpoint of accident. We use real time data. The real time data is event summarized for multiple instances and is fed into the classifier for either alerting in case of accident or warning in case of accident prevention. This project aims at solving the manual driven vehicle problem to alert the driver and also aims on being expandable for self-driven cars because accidents can happen to anyone,anything or anyway.

Keywords—EDR, Multisensor Fusion, Edge Summarization

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LIST OF ABBREVIATIONS

ACC	Accelerometer Sensor
ADC	Analog-to-Digital Converter
AT	Attention (AT Commands)
BLE	Bluetooth Low Energy
CS	Crash Sensor
EDR	Event Data Recorder
ESP-IDF	Espressif IoT Development Framework
ESP32-S3	Espressif 32-bit System on Chip (S3 Variant)
FS	Flame Sensor
GPIO	General Purpose Input/Output
GPS	Global Positioning System
GSM	Global System for Mobile Communications
GY	Gyroscope Sensor
IDE	Integrated Development Environment
IMU	Inertial Measurement Unit
ML	Machine Learning
MS	Magnetometer Sensor
PWM	Pulse Width Modulation
SIM	Subscriber Identity Module
SOS	Save Our Souls
SPI	Serial Peripheral Interface
UART	Universal Asynchronous Receiver–Transmitter

1. INTRODUCTION

"EDR (Event Data Recorder) Based Intelligent Vehicle Accident Prediction with Multisensor Fusion and Edge Summarization" is a project that focuses on pre-event and post-event analysis and predict the accident and log it. The MultiSensor Fusion gives more accurate data and we can use that data to feed into a real time frame. The edge processing eliminates the unnecessary flagged data that we do not need while analyzing and alerting the system. The traditional project lacked the fusion of two technologies in a single EDR, which just doesn't make this a logger rather make it an intelligent predicting logger further explained in block diagram of methodology.

1.1. Background

Conventional vehicle EDR lacked the intelligent decision making capabilities. The project highlights an intelligent accident intelligent Vehicle Accident Prediction with Multisensor Fusion and Edge Summarization. The accuracy and timely emergency response results in a safety driven concern for the vehicles. The alert system that is classified accordingly makes the use case of this project more practical and more reliable compared to the traditional EDR. Multisensor fusion and edge summarization can improve overall reliability which is more practical in real-world deployment.

1.2. Motivation

This project came into idea when there was a deadly bus accident in Trishuli where at least 54 people went missing after two passenger buses were swept away by a mudslide into the rain-swollen Trishuli River near Simaltal. Nepal police, Armed Police Force and Nepal Army personnel worked tirelessly to find the bus in the swelling river and continuous rainfall but the effort went into vain after the search had no result. Had the rescuers or finders had better technology, the last data recorded, the search would have been more predictive. The timely SOS would have been sent early. This is just an example of a larger problem that occurs in day to day life in a world moving so fast. There also are many instances where the drivers aren't alerted, the state at which they are driving compared to a probabilistic scenario can be dangerous, if we find those pattern and pre-alert the driver , the accident case can be

reduced and possibly save life of thousands travelling. This is why we chose "EDR-Based Intelligent Vehicle Accident Prediction with Multisensor Fusion and Edge Summarization"

1.3. Problem Statement

Existing systems for alerting or logging rely on single sensors or manual reporting, which makes them prone to false alarming and missed detection. The existing system depends on cloud based processing which in case of critical situations is very unrealistic and illogical because the delay in the immediate response required case often lead to major casualties. Safety, risk management and reliability are our main concerns overall. The lack of multisensor Fusion, no edge ML, poor logging are often not considered till date, even if those projects are never brought into a single module that can solve a larger problem scenario. By trying to integrate all the aforementioned problem's solutions into a single module we have tried to solve the existing problem.

1.4. Objectives

The objectives of this project are as follows:

1. To detect vehicle accidents or predict possible accident scenarios using Multi-Sensor Fusion and a Machine Learning model (Random Forest) implemented on a microcontroller using a TinyML approach, and to alert the driver or concerned authorities in real time.
2. To log possible accidental parameters or critical spikes in sensor data during an accident or a potential accident scenario for further analysis.

1.5. Scope and Limitations

1.5.1. Scope

The intelligence, detection and logging mechanism are the key features included in our project. We have used technologies like Multisensor Fusion, Edge summarization and Machine Learning model implemented on an ESP32 microcontroller using the TinyML approach. The system performs real-time data acquisition, local processing, alert generation and logging of critical sensor parameters during accident and pre-accident scenarios. The scope of this work is limited to small-scale prototype implementation and controlled testing conditions. The system does not include full-scale vehicle integration, cloud-based analytics, or legal emergency response systems.

1.5.2. Limitations

The project has a lot of scope, but due to time constraints and limited resources, some major components cannot be implemented in this phase. The addition of a camera module and accident detection through image classification using machine learning cannot be implemented yet. Limited resources also restrict us to using simple models rather than more complex ones at this stage of the project. In the future, with adequate time, computational power, and resources, advanced machine learning models along with camera-based image classification can be integrated to enhance accident detection accuracy.

2. LITERATURE REVIEW

2.1. Literature Review

Amin et al. [1] proposed an accident detection system that utilizes deceleration data from low-cost Micro Electro Mechanical Systems (MEMS) based Inertial Measurement Unit (IMU). Their research demonstrates that the system can accurately detect collisions and maintain location tracking during Global Positioning System (GPS) outages, successfully transmitting critical information to a base station.

Furthering the integration of connectivity, Kumar et al. [2] presented an IoT-based automotive accident detection and classification (ADC) system. By fusing smartphone-built-in sensors with connected external sensors, this system not only detects accidents but also classifies the type of collision. This detailed reporting improves the efficacy of emergency medical services (EMS), fire departments, and towing services by allowing for more precise resource planning.

Regarding data management, Yao and Atkins [3] introduced the "Smart Black Box" (SBB), which enhances traditional low-bandwidth logging with value-driven, high-bandwidth data capture. The SBB utilizes a deterministic Mealy machine to cache short-term data buffers based on similarity and information value. By formulating compression as a constrained multi-objective optimization problem, the system prioritizes high-value recordings and discards redundant data to optimize finite storage.

Predictive modeling is addressed by Yang et al. [4], who employed a Random Forest algorithm to predict the severity of traffic accidents. By incorporating four key characteristics such as location, accident form, road information, and driving speed into their model, they achieved high performance in data classification, resulting in a more efficient and accurate predictive framework.

This project proposes an integrated vehicle safety system that combines accident prediction and detection with a robust data logging framework for forensic investigation. By utilizing a Random Forest algorithm, the system can identify potential risks and detect vehicle accidents in real-time, capturing critical pre-crash and post-crash telemetry. To ensure the accuracy of these observations, the system employs a linear Kalman filter to fuse data from the Accelerometer Sensor (ACC), Gyroscope Sensor (GY), and GPS, effectively minimizing sensor noise and measurement errors.

Furthermore, the system addresses data management challenges through an event summa-

rization technique. This method prioritizes the storage of relevant incident data, successfully reducing overall storage capacity requirements by half without compromising the integrity of the information needed for future investigations.

3. SYSTEM ARCHITECTURE AND METHODOLOGY

3.1. Proposed System Architecture

3.1.1. Proposed System Block Diagram

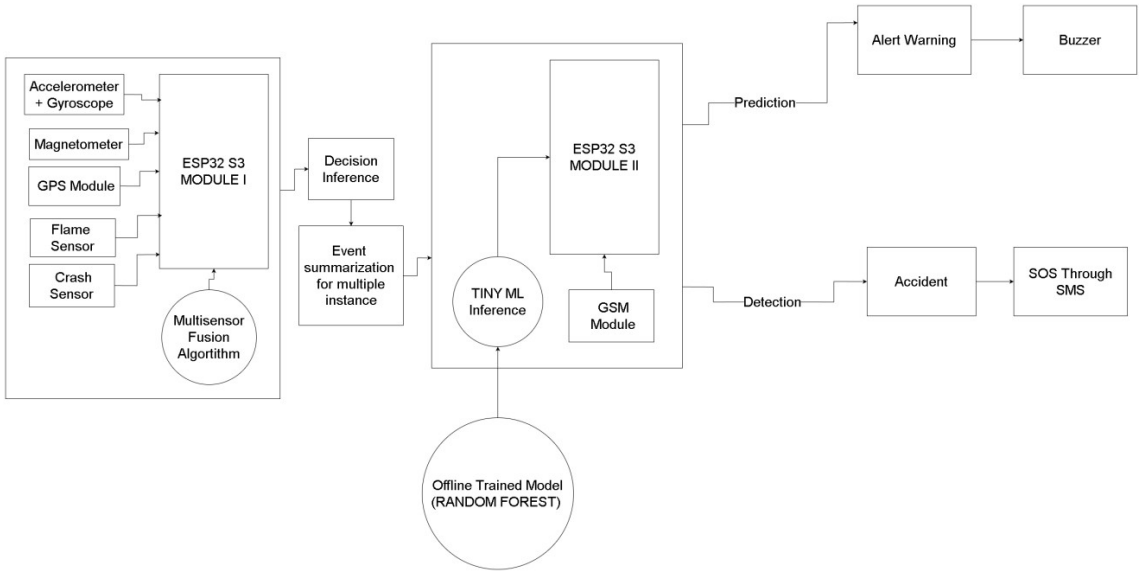

Figure 3.1.: *Block Diagram of Proposed System Architecture*

3.2. Working Principle

The proposed system uses a combination of multisensor fusion and TinyMachine Learning (ML)-based event classification (Random Forest) to monitor vehicles in pre-event and post-event analysis in real time, responding to potential accidents and generating alerts when necessary. The system is built around two microcontrollers, with one responsible for multisensor fusion and the other for verifying accident parameters via the ML model for prediction or alert.

The Espressif 32-bit System on Chip (S3 Variant) (ESP32-S3) Module I acquires continuous data from multiple sensors including ACC, GY, Magnetometer Sensor (MS), GPS, Flame Sensor (FS), and Crash Sensor (CS). These sensors collectively provide compre-

hensive information regarding the motion, orientation, location, and critical environment conditions of a vehicle. Significant deviations in sensor data are forwarded to the second module using decision inference.

A multisensor fusion algorithm based on the Kalman Filter is employed, integrating readings from all sensors to produce robust and reliable state estimation while minimizing noise and transient errors. Features of potential abnormal events are extracted from raw sensor readings, including acceleration magnitude, orientation angles, sudden speed changes, and activation of crash or flame sensors, forming the input for ML-based classification.

The ESP32-S3 Module II performs the ML inference to classify events as normal, warning, or accident. For normal events, the system continues monitoring without intervention. For warning events, the system triggers a local alert such as a buzzer. When an accident is detected, the system activates the Global System for Mobile Communications (GSM) module to send a Save Our Souls (SOS) message to predefined emergency contacts. A brief observation window ensures persistent abnormal conditions are confirmed before sending SOS signals, reducing false alarms.

Overall, the system integrates real-time sensor monitoring, robust data fusion, and lightweight ML inference to provide a reliable, fast, and energy-efficient solution for intelligent vehicle accident detection. Preventive warnings and emergency communication improve vehicle safety while maintaining low computational requirements suitable for microcontroller-based embedded platforms.

3.3. Kalman Filter Algorithm

The Kalman Filter is an optimal recursive estimation algorithm that simplifies the computational process of data fusion by introducing assumptions regarding system dynamics, state evolution, and the statistical properties of noise and estimation errors [5]. It provides an efficient solution to the linear quadratic estimation problem for systems affected by stochastic disturbances.

The Kalman Filter formulates estimates of the internal state of a linear dynamic system by processing a sequence of noisy measurements. The system is assumed to be disturbed by zero-mean Gaussian white noise, and the filter recursively updates the state estimates as new measurements become available [6]. Its predictor–corrector structure can be divided into two distinct phases:

- Time Update (Prediction)
- Measurement Update (Correction)

3.3.1. Assumptions

The Kalman Filter operates under the following assumptions [5]:

1. Linear system dynamics:

$$\mathbf{s}_t = \mathbf{A}\mathbf{s}_{t-1} + \mathbf{B}\mathbf{u}_t + \mathbf{w}_t \tag{3.1}$$

2. Linear measurement model:

$$\mathbf{z}_t = \mathbf{H}\mathbf{s}_t + \mathbf{v}_t \tag{3.2}$$

3. Process and measurement noises are mutually independent.

3.3.2. Time Update (Prediction Phase)

State Prediction

$$\hat{\mathbf{s}}_{t|t-1} = \mathbf{A}\hat{\mathbf{s}}_{t-1|t-1} + \mathbf{B}\mathbf{u}_t \tag{3.3}$$

Covariance Prediction

$$\mathbf{P}_{t|t-1} = \mathbf{A}\mathbf{P}_{t-1|t-1}\mathbf{A}^T + \mathbf{Q} \tag{3.4}$$

3.3.3. Measurement Update (Correction Phase)

Kalman Gain

$$\mathbf{K}_t = \mathbf{P}_{t|t-1}\mathbf{H}^T \left(\mathbf{H}\mathbf{P}_{t|t-1}\mathbf{H}^T + \mathbf{R}\right)^{-1} \tag{3.5}$$

Innovation (Measurement Residual)

$$\mathbf{y}_t = \mathbf{z}_t - \mathbf{H}\hat{\mathbf{s}}_{t|t-1} \tag{3.6}$$

State Update

$$\hat{\mathbf{s}}_{t|t} = \hat{\mathbf{s}}_{t|t-1} + \mathbf{K}_t\mathbf{y}_t \tag{3.7}$$

Covariance Update

$$\mathbf{P}_{t|t} = (\mathbf{I} - \mathbf{K}_t\mathbf{H})\,\mathbf{P}_{t|t-1} \tag{3.8}$$

3.4. Random Forest Machine Learning Model

A random forest is a classifier consisting of a collection of tree-structured classifiers $\{h(x, \Theta_k), k = 1, \dots\}$ where the $\{\Theta_k\}$ are independent identically distributed random vectors and each tree casts a unit vote for the most popular class at input x [7].

The common element in all of these procedures is that for the kth tree, a random vector Θ_k is generated, independent of the past random vectors $\Theta_1, \dots, \Theta_{k-1}$ but with the same distribution; and a tree is grown using the training set and Θ_k, resulting in a classifier $h(x, \Theta_k)$ where x is an input vector. For instance, in bagging the random vector Θ is generated as the counts in N boxes resulting from N darts thrown at random at the boxes, where N is the number of examples in the training set. In random split selection, Θ consists of a number of independent random integers between 1 and K. The nature and dimensionality of Θ depends on its use in tree construction. After a large number of trees is generated, they vote for the most popular class. These procedures are called random forests [8].

3.4.1. Random Forest Convergence

Given an ensemble of classifiers $h_1(x), h_2(x), \dots, h_K(x)$, and with the training set drawn at random from the distribution of the random vector (Y, X), define the margin function as:

$$\text{mg}(X, Y) = \text{avg}_k I(h_k(X) = Y) - \max_{j \neq Y} \text{avg}_k I(h_k(X) = j), \tag{3.9}$$

where $I(\cdot)$ is the indicator function. The margin measures the extent to which the average number of votes at (X, Y) for the correct class exceeds the average vote for any other class. The larger the margin, the more confidence in the classification. The generalization error is given by:

$$PE^* = P_{X,Y}(\text{mg}(X, Y) < 0), \tag{3.10}$$

where the subscripts X, Y indicate that the probability is over the X, Y space.

In random forests, $h_k(X) = h(X, \Theta_k)$. For a large number of trees, it follows from the Strong Law of Large Numbers and the tree structure that:

Theorem 1. As the number of trees increases, for almost all sequences $\Theta_1, \dots$, PE^* converges to

$$P_{X,Y}\Big(P_\Theta(h(X, \Theta) = Y) - \max_{j \neq Y} P_\Theta(h(X, \Theta) = j) < 0\Big). \tag{3.11}$$

This result explains why random forests do not overfit as more trees are added, but produce a limiting value of the generalization error [7].

3.4.2. Key Features of Random Forests

- Its accuracy is as good as AdaBoost and sometimes better [7].
- It is relatively robust to outliers and noise [7].
- It is faster than bagging or boosting [7].
- Provides useful internal estimates of error, strength, correlation, and variable importance [7].
- Simple and easily parallelized [8].

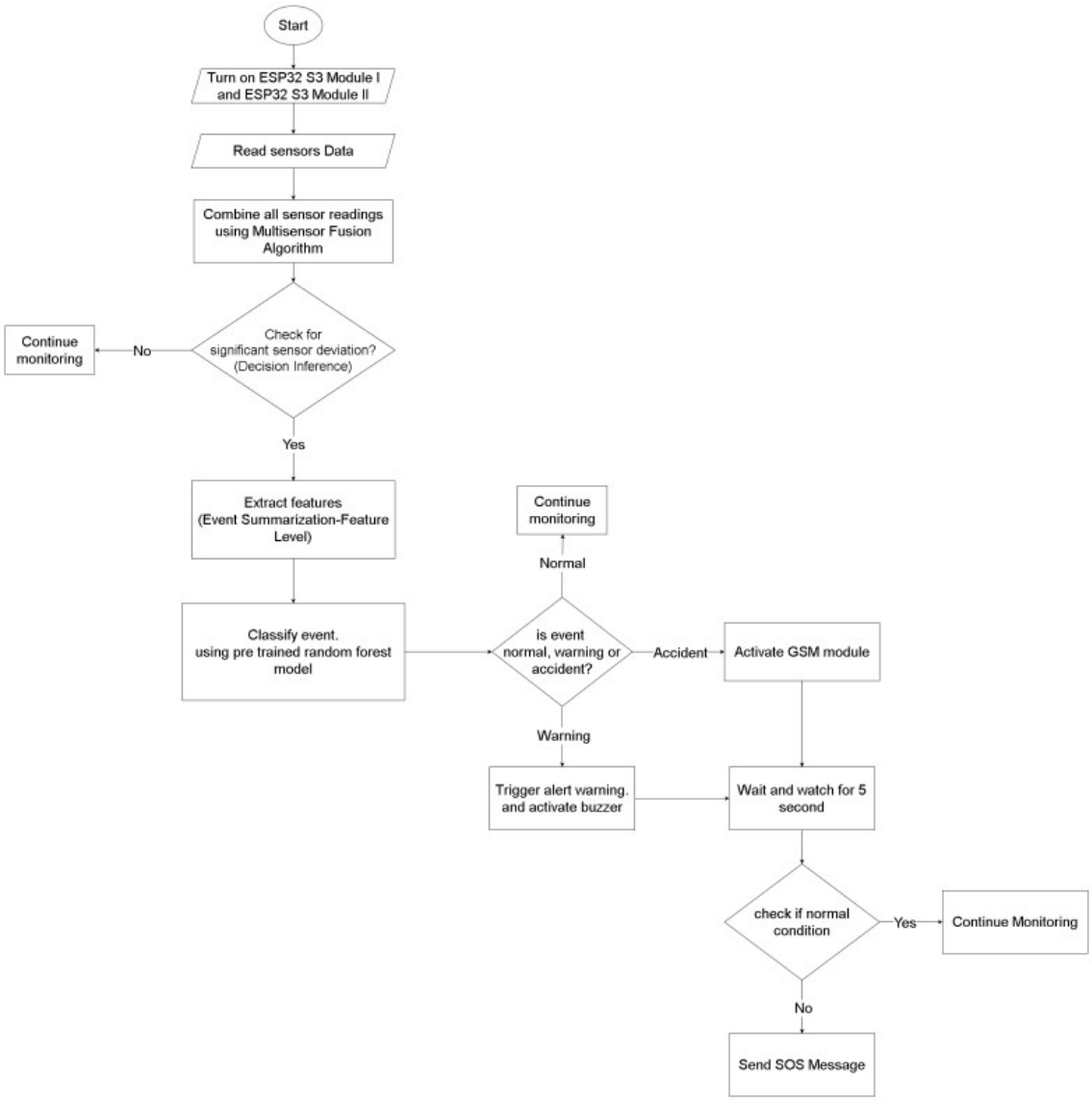

Figure 3.2.: *Flowchart of Proposed System Architecture*

4. IMPLEMENTATION DETAILS

4.1. Hardware Implementation

Accelerometer and Gyroscope Sensors

An ACC and GY together form an IMU used to measure linear acceleration and angular velocity of the vehicle. These sensors continuously monitor dynamic motions such as acceleration, braking, skidding, tilting, sharp turns, rollover, and collision forces.

Reasons to Use Accelerometer and Gyroscope

- Measures both linear and rotational motion of the vehicle.
- Enables accurate detection of sudden impacts and abnormal movements.
- Provides continuous, low-noise motion data suitable for real-time processing.
- Low power consumption and minimal computational overhead.
- Compact, cost-effective, and easily integrable with microcontrollers.
- Highly compatible with rule-based and ML-based accident detection systems.

The combined motion data from the ACC and GY allows effective feature extraction for detecting unsafe driving behavior, loss of vehicle stability, and crash events, making the IMU a key component in accident prediction and vehicle safety applications.

Suitable Accelerometer and Gyroscope Sensor: MPU6050

The MPU6050 is a 6-axis MEMS IMU that integrates a 3-axis ACC and a 3-axis GY along with an internal Digital Motion Processor (DMP). It outputs motion data digitally via the I^2C interface. By combining acceleration and rotational data, it effectively detects sudden motion changes and crash occurrences.

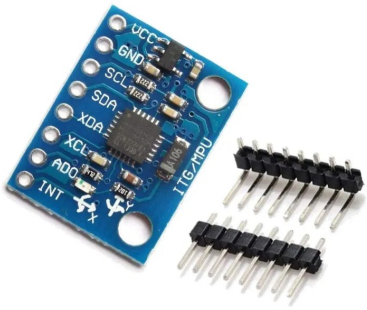

Figure 4.1.: *MPU6050 Accelerometer and Gyroscope Module*

Magnetometer Sensor

A MS measures the strength and direction of a magnetic field, typically the Earth's magnetic field, to determine vehicle orientation and heading.

Reasons to Use Magnetometer

- Provides absolute heading reference.
- Improves long-term stability of motion estimation.
- Low power consumption.
- High-resolution digital output.
- Cost-effective and ML-friendly.

HMC5883L MEMS-Based Magnetometer

The HMC5883L is a 3-axis MEMS MS that uses magnetoresistive sensing elements to measure magnetic field components along the X, Y, and Z axes and provides digital output through the I^2C interface.

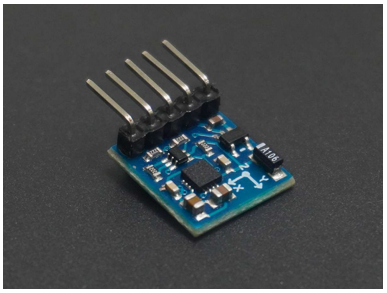

Figure 4.2.: *HMC5883L Magnetometer Module*

GPS Sensor

A GPS sensor determines the absolute geographical position of a vehicle by receiving signals from multiple satellites. It provides latitude, longitude, speed, altitude, and timestamp information essential for vehicle tracking and accident localization.

Reasons to Use GPS Module

- Provides accurate real-time latitude and longitude.
- Measures vehicle speed and heading.
- Enables precise accident location reporting.
- Low power consumption for continuous tracking.
- Stable and reliable data output for ML processing.

Figure 4.3.: *GPS NEO-6M Module*

Flame Sensor

A FS detects the presence of fire by sensing infrared radiation emitted during combustion. It is critical for identifying fire hazards following vehicle collisions.

Reasons to Use Flame Sensor

- Enables early fire detection.
- Fast response time.
- Simple microcontroller interface.
- Low power consumption and cost.
- Suitable for rule-based and ML-based decision systems.

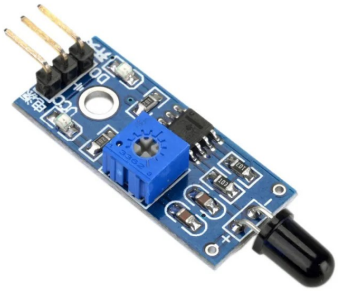

Figure 4.4.: *Flame Sensor Module*

Crash Sensor

A CS, also known as an impact sensor, detects sudden mechanical shocks or collision forces acting on the vehicle.

Reasons to Use Crash Sensor

- Immediate collision detection.
- High reliability in impact sensing.
- Very low processing requirement.
- Fast response for emergency systems.
- Cost-effective and durable.
- Strong support for decision inference.

Figure 4.5.: *Crash Sensor Module*

GSM Module

A GSM module enables embedded systems to send and receive data over cellular networks using a Subscriber Identity Module (SIM). It allows communication with predefined contacts such as emergency services and family members.

GSM Module (SIM800L)

The GSM module communicates with the controller via Universal Asynchronous Receiver–Transmitter (UART) using Attention (AT Commands) (AT) commands. Once a SIM is inserted, the module registers with the nearest cellular base station. During emergency events such as crashes or fire detection, the module automatically transmits SMS alerts to predefined mobile numbers.

Reasons to Use GSM Module

- Enables long-distance communication without internet dependency.
- Real-time emergency alert transmission via SMS.
- Reliable operation in rural and remote areas.
- Simple microcontroller integration.
- Low power consumption.

- Cost-effective and widely supported.

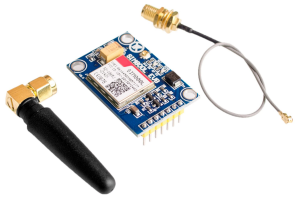

Figure 4.6.: *GSM SIM800L Module*

ESP32-S3 Microcontroller

The ESP32-S3 is a high-performance, low-power microcontroller developed by Espressif Systems for advanced embedded and IoT applications. It integrates wireless connectivity and AI acceleration features, making it suitable for real-time sensing and edge intelligence.

ESP32-S3 Module

The ESP32-S3 is based on a dual-core Xtensa® 32-bit LX7 processor operating up to 240 MHz. It includes built-in Wi-Fi and Bluetooth Low Energy (BLE), along with rich peripheral support such as Serial Peripheral Interface (SPI), I^2C, UART, Analog-to-Digital Converter (ADC), Pulse Width Modulation (PWM), and General Purpose Input/Output (GPIO)s. Support for external flash and PSRAM enables efficient handling of sensor data and ML models.

Reasons to Use ESP32-S3

- High processing capability.
- Optimized for ML inference.
- Supports multiple sensors simultaneously.
- Low power operation.

How This Is Compatible with Machine Learning

The ESP32-S3 is specifically designed for edge ML applications. Its LX7 processor supports vector instructions that accelerate mathematical operations used in ML inference. Frameworks such as TensorFlow Lite for Microcontrollers and ESP-DSP enable deployment of trained models directly on the device. In this project, the ESP32-S3 performs real-time sensor fusion, feature extraction, and decision inference locally, reducing latency and eliminating cloud dependency. This makes it ideal for safety-critical applications such as crash and fire detection.

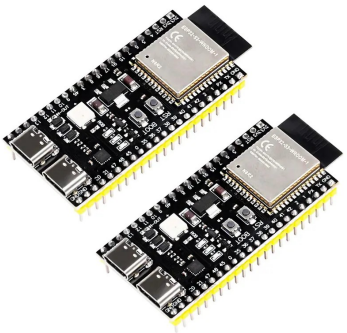

Figure 4.7.: *ESP32-S3 Module*

4.2. Software Implementation

The software implementation involves programming the ESP32-S3 microcontroller using the Arduino Integrated Development Environment (IDE) and Espressif IoT Development Framework (ESP-IDF). The code integrates sensor data acquisition, preprocessing, feature extraction, and decision-making algorithms for accident and fire detection. The ML model is trained offline using Python-based libraries such as NumPy and Pandas, and then converted to a format compatible with the ESP32-S3 for deployment. The system continuously monitors sensor inputs, processes the data in real-time, and triggers alerts via the GSM module when hazardous events are detected.

Arduino IDE

Arduino IDE is a widely used software platform for writing, compiling, and uploading programs to microcontroller boards such as Arduino and NodeMCU. It provides a simple and intuitive environment that allows developers to efficiently develop embedded applications. The IDE includes a built-in code editor with syntax highlighting, a compiler, and tools for uploading firmware to hardware devices. It also supports a large number of libraries, enabling easy integration of sensors, communication modules, and peripheral devices. Arduino IDE is compatible with multiple operating systems, making it accessible and convenient for developers.

TensorFlow

TensorFlow is an open-source software framework developed by Google for numerical computation and data processing. It provides a flexible platform for handling large datasets, performing mathematical operations, and building computational models. TensorFlow offers a rich set of libraries and tools that help developers process and analyze data efficiently. In this project, it is used as a supportive software tool for data handling and model development during the system design and evaluation phase.

VS code IDE

VS Code IDE is a powerful and versatile code editor developed by Microsoft. It provides a rich set of features for writing, debugging, and managing code across various programming languages. VS Code supports extensions that enhance its functionality, including support for Python development, which is essential for data analysis and ML model development in this project. The IDE offers integrated terminal access, version control integration, and customizable settings, making it a preferred choice for developers working on complex software projects.

Jupyter Notebook

Jupyter Notebook is an open-source web application that allows users to create and share documents containing live code, equations, visualizations, and narrative text. It is widely used for data analysis, scientific computing, and machine learning tasks. In this project, Jupyter Notebook serves as a supportive tool for exploratory data analysis, feature engineering, and model training. It provides an interactive environment where developers can write and execute Python code, visualize data using libraries like Matplotlib and Seaborn, and document their findings in a structured format.

4.3. Datasets

The proposed system will be using a sensor-based dataset to train a TinyML model relying on the accelerometer, gyroscope, GPS data. The dataset we use will not be the data under crash condition as these kinds of data are difficult to find on internet and difficult to collect ourselves. The better option would be to use the dataset under normal driving conditions. The data was found on the website "Kaggle". This data contains the motion sensor-based data collected during various driving conditions including normal vehicle movement sharp turns, road bumps which are essential for the accurate prediction of accident. [9]

As given on the website, the devices were fitted on the vehicle as shown in the figure below. Data of many different components including accelerometer, gyroscope, GPS, camera was collected. We plan to use only the data of accelerometers, gyroscope and GPS. [10] The data were produced in three different vehicles, with three different drivers, in three different environments in which there are three different surface types, in addition to variations in conservation state and presence of obstacles and anomalies, such as speed 20 bumps and potholes. The data was collected from three different types of roads i.e. Asphalt Road, Dirt Road and Cobblestone Road. The dataset contains the data of good roads, bad roads,

and regular roads. Speed bumps in Cobblestone and Asphalt roads are also included in the dataset. It is also inclusive of driving events, such as lane change, braking, skidding, aquaplaning, turning right or left etc.

5. EXPECTED OUTCOMES

1. **Accident Prediction & Crash Detection**
   The system is expected to analyze multisensory fused data including ACC, GY, heading direction, fire detection (FS), and crash impact signals (CS) to compute a real-time accident risk-score. Based on this risk score, the system will predict the potential accident scenarios and detect crash occurrences under impact conditions using ML-based inference.
2. **EDR - Event Data Recorder**
   The Event Data Recorder (EDR) module is expected to continuously record and store structured sensor and event data in real time. When an accident occurs, the EDR preserves critical event information including sensor readings and system decisions. The purpose of this module is to provide reliable event data for post-accident analysis and investigation.
3. **Alert and SOS Signals**
   The system is expected to trigger real-time alerts or warning signals such as buzzer activation to notify the driver upon detecting high risk-score scenarios for accidents. In the event of a confirmed accident, the system generates SOS signals and transmits them to nearby helplines via the GSM module.

A. PROJECT BUDGET

The total budget required for the successful completion of the project is estimated to be between **NPR 8000 - NPR 11000**. This budget covers various aspects of the project, including hardware purchases, component materials, software services, and miscellaneous expenses.

A.1. Bill of Materials (BOM)

This section details all components that will be integrated into the final product/system. These are the materials that constitute the deliverable hardware (if any).

Table A.1.: *Project Budget*

SN	Components	Qty	Unit Cost (NPR)	Total (NPR)
1	ESP32 S3	2	1500	3000
2	GSM800L	1	1000	1000
3	GPS	1	800	800
4	MPU6050	1	700	700
5	HMC5883L	1	450	450
6	Flame Sensor	1	320	320
7	Crash Sensor	1	100	100
8	SIM Card	1	100	100
9	Bread Board	1	450	450
10	Resistor	1	150	150
11	Buzzer	1	100	100
12	Wire	1	200	200
13	Power Supply	1	400	400
			Total	**7770**

B. PROJECT TIMELINE

The project will be executed over a period of approximately 6 months, divided into several key phases. Each phase includes specific tasks and milestones to ensure steady progress toward project completion.

B.1. Gantt Chart

This is the estimated timeline for the project, detailing the key phases and milestones. The project is structured into several stages, each with specific tasks and deliverables.

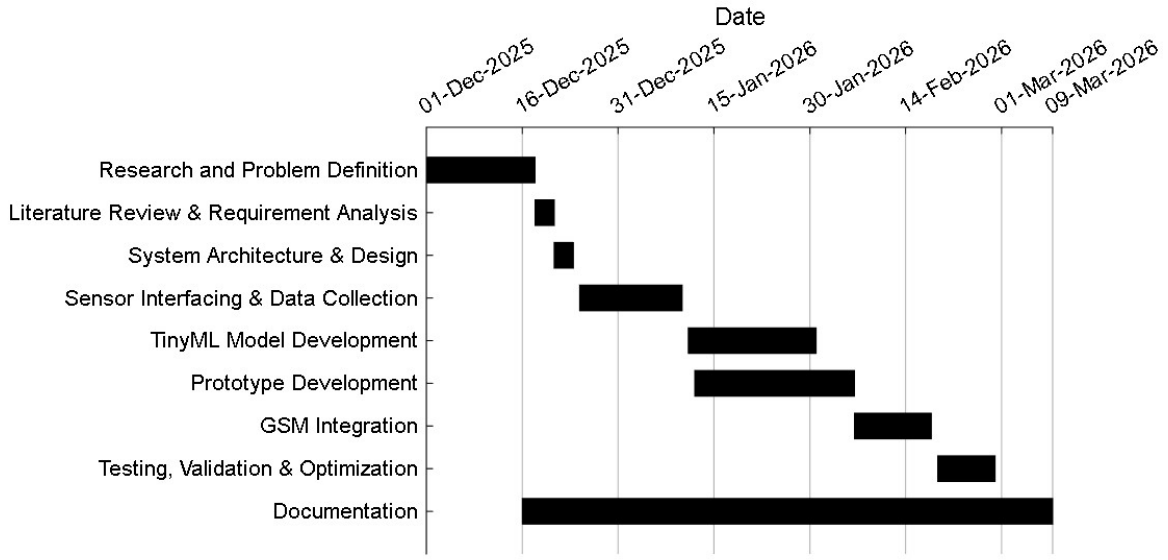

Figure B.1.: *Project Gantt Chart*

C. FEASIBILITY

This project is proposed to be implemented using hardware components such as the ESP32-S3 microcontroller, ACC, GY, MS, FS, CS, ultrasonic sensor, GPS module, and GSM module. These components are readily available in the market and are cost-effective, making the system economically feasible for real-world deployment.

The software tools used in this project are free and open-source. Programming of the ESP32-S3 is carried out using the Arduino IDE and ESP-IDF. For data analysis and ML model development, Python-based libraries such as NumPy and Pandas are used. These tools support sensor data processing, feature extraction, and model training during the learning phase of the project.

The dataset required for training and validating the prototype is planned to be obtained from open-source platforms such as Kaggle, along with real-time data collected from the sensors during testing. This combination helps improve model reliability and provides insight into real-world sensor behavior.

The project requires a SIM card and a GSM-enabled mobile network to function effectively. The system is installed in a vehicle with a SIM card inserted into the GSM module, enabling communication over the mobile network. This allows the ESP32-S3 to send alerts, SOS messages, and location information to predefined contacts or emergency services during accident or fire detection events.

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