Smart Glasses for Navigation and Obstacle Detection for Visually Impaired Using Ultrasonic Sensors, Camera, and Edge AI

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Project Proposal Report

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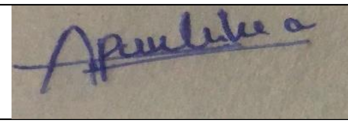
DECLARATION

Student	Signature
IT21821486 – A.S.G. Punchihewa	

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Signature of the Supervisor	Date

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Signature of the Co-Supervisor	Date

ABSTRACT

Visual impairment significantly impacts independent mobility and environmental awareness, often limiting access to education, employment, and social interaction. The project will be focused on developing an assistive system that can enhance autonomy in visually impaired individuals by detecting real-time objects, measuring distances, and providing intuitive feedback. The system incorporates ultrasonic sensors and a camera with embedded machine learning-TinyML and Edge AI-which makes it compact and wearable in the form of smart glasses. By fusing multi-sensor data with advanced computing, the system provides voice and haptic feedback to enable safer navigation both indoors and outdoors. Ultrasonic sensors precisely measure the distance from the nearby obstacles, hence detecting objects within a range from 2 cm to 4 meters.

While doing so, simultaneously, visual data is provided by a camera for the purpose of object classification, such as doors, stairs, pedestrians, and vehicles by lightweight CNNs optimized for low-power hardware. This dual sensor ensures that whatever limitations in the performance may come from low-light conditions are dealt with by supplementing the visual data with ultrasonic data. With Edge AI, all sensor inputs are processed locally, removing dependencies on cloud computing, while ensuring privacy, low latency, and real-time operation. The Machine learning models shall be optimized for TinyML using transfer learning, pruning, and quantization techniques that successfully deploy the model on resource-constrained microcontrollers and low-power SoC devices. The module for camera-based object detection shall provide the maximum possible accuracy while trying to keep power consumption as low as possible to perform real-time inference. Kalman filter ultrasonic and camera data fuse by refining distance estimations for higher accuracy of the objects detected correctly. For example, it offers adaptive feedback by voice synthesis and also by the use of vibration motors that are embedded in the frame of the glasses, such as, "Table ahead, 1 meter." Intensity and location of vibrations guide the users around obstacles so that an intuitive response to environmental hazards is assured. Besides this, basic navigation features such as GPS-assisted route guidance further support user mobility.

This work investigates the integration of low-cost sensors, embedded machine learning, and user-centered design in developing an innovative, scalable assistive technology. In the proposed solution, the removal of cloud dependency will ensure affordability and accessibility, making it a potential tool to foster independence among the visually impaired. Additionally, a mobile app is used to deliver voice feedback, enhancing the user experience by providing real-time information. Future work will focus on refining object recognition, improving localization through SLAM, and conducting user trials to optimize the feedback mechanism

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1. INTRODUCTION

Over 2.2 billion people in the world have visual impairments, notably limiting independent mobility and preventing access to real-time environmental information. The standard white canes and guide dogs are important but always have inherent limitations: they cannot detect obstacles that are either far away or overhead, such as overhanging branches or moving vehicles. Moreover, little contextual awareness regarding object types, such as distinguishing between stairs and doors, can be provided. Thereafter, most visually impaired individuals face complex challenges in their efforts toward safe and efficient navigation.

Advances in embedded systems, computer vision, and edge computing have opened up opportunities to fill these gaps through intelligent assistive technologies. This project proposes a wearable system that is designed to enhance spatial awareness and the detection of obstacles in visually impaired individuals. It integrates ultrasonic sensors with a camera-based object detection module using TinyML-optimized machine learning models that classify objects in real time. The ultrasonic sensors provide high-accuracy range measurements, while the camera performs object recognition, including pedestrians, furniture, and doorways. On deploying an Edge AI-enabled system with machine learning models, the processing is totally localized; hence, real-world performance, privacy, and efficiency are realized on any given day without the system necessarily needing to be connected to a cloud system. Feedback reaches users naturally through voice warnings and haptic indications that let users move with safe independence through indoor and outdoor environments. This system integrates multi-sensor data, light AI, and user-oriented design to create wearable, practical, and scalable devices for the improvement of mobility and quality of life in visually impaired individuals.

2. BACKGROUND & LITERATURE SURVEY

The development of assistive technologies for visually impaired individuals has made significant strides in recent years, primarily driven by advances in sensor systems, machine learning, and edge computing. This section explores the foundational concepts, technological advancements, and the existing gaps that shape the design of the proposed smart glasses system.

Visual impairment significantly impacts daily life, affecting over 2.2 billion individuals globally (WHO, 2023). Traditional aids like white canes and guide dogs provide tactile feedback, but they are limited in their ability to detect non-physical obstacles (e.g., overhanging branches) or provide contextual information about objects (e.g., distinguishing stairs from doors). These limitations reduce independence and confidence, particularly in unfamiliar environments or crowded spaces.

Early solutions, such as the UltraCane, augmented tactile feedback with ultrasonic sensors to detect obstacles up to 4 meters away. However, these devices were limited in functionality, unable to recognize specific object types or account for obstacles at greater distances [1]. Advances in sensor technology introduced infrared (IR) and LiDAR systems for higher-resolution spatial mapping, as demonstrated by the Sunu Band [2]. While effective in detecting obstacles, these systems often faced high power consumption, making them impractical for continuous, long-term use.

The integration of cameras and machine learning has significantly improved object detection capabilities. Systems like Microsoft's Seeing AI leverage smartphone cameras to recognize objects, but these solutions rely on cloud-based processing, which introduces latency and privacy concerns. Edge AI platforms, which process data locally, address these issues by providing real-time feedback. The use of lightweight convolutional neural networks (CNNs), such as YOLO-Tiny, has further improved the feasibility of on-device object detection while reducing computational overhead [3].

One example of a vision-based system is the wearable camera for urban obstacle detection, which demonstrated an 85% accuracy rate for detecting common objects such as pedestrians and traffic lights. However, these vision-only systems are often challenged by low-light conditions and higher power consumption, limiting their application in real-time wearable devices [4].

Combining multiple sensors can overcome the limitations of individual modalities. For instance, LiDAR and RGB-D camera data have been fused to achieve high-accuracy obstacle detection [5]. Similarly, studies have demonstrated the utility of pairing ultrasonic sensors with thermal cameras to enhance obstacle detection reliability in dynamic environments [6]. One notable approach involves using Kalman filters to reconcile measurements from ultrasonic sensors and cameras, providing more accurate distance estimations in real-time environments [7].

TinyML frameworks have transformed the capabilities of embedded systems by enabling machine learning on low-power, resource-constrained devices. Models like MobileNetV2, when pruned and optimized for real-time performance, can run efficiently on microcontrollers and small edge devices, offering high accuracy in a range of tasks, including object recognition and environmental sensing [8]. This shift to on-device AI ensures faster processing, reduces dependence on cloud infrastructure, and enhances data privacy, all of which are crucial for assistive technologies [9].

The integration of TinyML models into assistive devices, such as the pruned MobileNetV2 on an Arduino Nano 33 BLE Sense, has shown promising results in real-time applications with minimal power consumption [10]. These advancements are foundational for creating efficient, affordable, and scalable solutions for visually impaired individuals.

The review of existing technologies reveals the potential of combining low-cost sensors, TinyML, and edge computing to create an accessible and effective assistive system for visually impaired individuals. By addressing the limitations of previous systems, such as power consumption and latency, this project aims to develop a practical, real-time solution for enhancing mobility and independence.

3. RESEARCH GAP

Feature	Edge AI & TinyML	Sensor Fusion (LiDAR + Ultrasonic)	Environmental Adaptability	Privacy (Local Processing)	Audio/Haptic Feedback	Wearable Device
Research A	✗	✗ (Ultrasonic-only)	✗	✗ (Cloud-based)	✗	✓
Research B	✗	✓	✓ (Limited lighting adaptation)	✗ (Cloud-dependent)	✗	✗
Research C	✓	✗ (Single sensor)	✗	✓	✓	✓
Research D	✓	✓	✓	✓	✗	✗
Research E	✗	✗ (Ultrasonic-only)	✗	✓	✓	✓
Proposed System	✓	✓	✓	✓	✓	✓

Research A: Navigation for Visually Impaired, MIT, 2020

Research B: Obstacle Detection via LiDAR, Stanford, 2022

Research C: Edge AI for Wearables, IEEE IoT, 2021

Research D: TinyML Sensor Fusion, ACM Sensys, 2023

Research E: Ultrasonic Navigation, UoP, 2021

Despite significant advancements in assistive navigation technologies, existing research exhibits several limitations that hinder optimal real-world implementation. A comparative analysis of previous studies reveals the following gaps:

1. Limited Integration of Edge AI & TinyML

    - Research A, B, and E do not leverage Edge AI or TinyML, relying on conventional processing methods.
    - While Research C and D incorporate Edge AI, only Research D explicitly utilizes TinyML for lightweight and efficient computations.
    - The proposed system addresses this by integrating both Edge AI and TinyML, ensuring low-latency, on-device processing for real-time responsiveness.

2. Incomplete Sensor Fusion Strategies

    - Research A and E rely solely on ultrasonic sensors, limiting their accuracy in obstacle detection.
    - Research C employs only a single sensor, which may reduce detection reliability.
    - Research B and D use sensor fusion, but further improvements in adaptability are required.
    - The proposed system enhances sensor fusion by effectively combining ultrasonic sensors, ensuring higher precision in obstacle detection.

3. Privacy and Local Processing Limitations

- Research A and B depend on cloud-based or cloud-dependent processing, which raises concerns about latency and data privacy.
- The proposed system ensures local processing, minimizing reliance on external cloud services, enhancing user privacy, and reducing processing delays.

4. Lack of Comprehensive Environmental Adaptability

- Research A, C, and E lack adaptability features, making them less effective in dynamic environments.
- Research B and D incorporate environmental adaptability, but their methods may not be optimal.
- The proposed system improves upon this by enhancing adaptability, ensuring robust performance in varying conditions.

5. Limited Audio/Haptic Feedback Implementation

- Research A and B do not incorporate audio or haptic feedback, making real-time navigation feedback less effective.
- Research C, D, and E include haptic/audio feedback, which enhances user interaction.
- The proposed system integrates multi-modal feedback (audio and haptic) to improve user awareness and navigation safety.

6. Wearable Device Implementation

- Research B and D do not focus on wearable designs, reducing usability for visually impaired users.
- Research A, C, and E integrate wearable solutions, but improvements are needed for seamless user experience.
- The proposed system ensures a wearable-friendly design, making it ergonomic and accessible for end users

4. RESEARCH PROBLEM

Despite the great achievements made so far in assistive technologies, visually impaired people still face some key challenges that limit their independence and mobility. The existing solutions, including white canes, guide dogs, and sensor-based wearables, fall short in most cases of providing comprehensive and actionable assistance. This project aims to solve the following open issues:

- Limited Environmental Context Awareness:

    Traditional aids, such as ultrasonic canes, typically detect obstacles but do not provide contextual information of object identification-for example, recognizing a pedestrian from a wall-or actionable guidance-for instance, "stairs ahead, 2 meters." This lack of detailed awareness about the environment due to the above seriously affects users' ability to make informed decisions independently in dynamic or unfamiliar environments.

- Trade-offs Between Accuracy and Power Efficiency:

    While this certainly provides impressive accuracy in object recognition, vision-based systems-particularly those using deep learning models, such as CNNs-require substantial computational resources and hence cannot be used within energy-constrained wearable devices. On the contrary, lightweight system designs that usually depend on rudimentary sensors-infrared or ultrasonic-ensure power efficiency, yet they compromise on the semantics of the event recognition.

- Latency and Privacy Concerns in Cloud-Dependent Systems:

    Most camera-driven assistive technologies rely on the cloud for object recognition and thus introduce inherent delays (≥ 500 ms), exposing sensitive user data to privacy risks. There is significant unmet demand for enabling real-time, on-device processing for such systems while ensuring both privacy and responsiveness on resource-limited hardware.

- Limitations of Sensor Fusion:

    Multi-sensor systems, like the fusion of ultrasonic sensors and cameras, improve the reliability of object detection. However, they are susceptible to several challenges, which includes synchronization errors, false positives due to environmental reasons such as rain or reflective surfaces, leading to degradation in performance and user experience. The development of appropriate cost-effective and power-efficient fusion strategies is highly necessary to overcome these limitations.

- Poor Multimodal Feedback Design:

  Most of the assistive systems are based on a single type of feedback, either voice or haptic. While powerful in certain contexts, the sole approach may overwhelm users in complex scenarios or be unable to address diverse user preferences related to reliance on either auditory or tactile information. A more subtle, multimodal feedback system is required that will offer intuitive, context-aware guidance, adaptive both to the environment and to the personal preferences of a user.

Research Questions

- Quantization and pruning TinyML optimization techniques are enabled to run high accuracy object detection models efficiently on edge devices that have very limited computational resources.
- How might multimodal feedback systems-using voice and haptic cues-be designed to give non-overwhelming navigation guidance that is intuitive and matched to the needs of visually impaired users?
- What sensor fusion strategies can be implemented with the purposes of power consumption minimization while considering robustness against environmental noise and hardware limitations?

It serves the general objective of technology design for inclusion in line with such global initiatives as the United Nations' SDGs on disability inclusion and thus may have an exponential impact on increasing the quality of life among the visually impaired all over the world.

5. OBJECTIVES

5.1. MAIN OBJECTIVES

The main objective of the work is to design and develop an intelligent assistive system for the visually impaired to improve their environmental awareness, navigation, and safety. This shall be realized through multi-sensors, embedded artificial intelligence AI, and user-centered feedback mechanisms. Key objectives include the following:

- Design a Cost-Effective Wearable Hardware System: - The system will be designed as a low-cost, wearable device that will integrate ultrasonic sensors and cameras to detect obstacles in real time with high accuracy, measure distances, and contextual identification of objects to improve navigation in diverse environments.

- On-Device Processing using TinyML and Edge AI: - Process sensor data in real time directly on the device using TinyML and Edge AI methods. This will ensure efficient object recognition without cloud systems and thus provides low latency and high user privacy.
- Design an Adaptive Multimodal Feedback System: - Develop a voice and haptic multimodal feedback system that will provide clear, intuitive guidance with regard to user preference and dynamic context of the environment. The system shall avoid overloading the user with information, being responsive, and of a nature that is easily interpretable in various situations.
- Optimize Power Efficiency and Computational Performance: -Improvement should emphasize the optimization of power consumption and computational performance for smooth and real-time operation on resource-limited embedded devices. This will involve studying ways of minimizing power consumption without affecting the efficiency of the system in natural environments.
- Test the System's Usability and Effectiveness in Real-World Applications: - Conduct formal user trials and performance tests to determine the practical usability, effectiveness, and user satisfaction of the system in real-world situations. The outcome of such trials will be the further improvement and refinement of the system.

5.2. SPECIFIC OBJECTIVES

- Design a power-efficient circuit for simultaneous sensor operation: The circuit should minimize power usage while enabling multiple sensors to operate at once, ensuring efficient energy consumption for long-term use.
- Train a lightweight object detection model using transfer learning on a custom dataset: A pre-trained model is fine-tuned using a custom dataset to accurately detect relevant objects, reducing the need for extensive training resources.
- Optimize the model with quantization and pruning: Quantization reduces model size by lowering precision, while pruning removes unnecessary parameters, making the model faster and more efficient.
- Implement voice alerts for object types and distances: Voice alerts provide instant feedback on detected objects and their distances, helping users navigate by hearing relevant information.
- Integrate haptic feedback for proximity and direction using vibration motors: Vibration motors offer tactile feedback to inform users about nearby obstacles and their direction, enhancing navigation without visual cues.

- Achieve real-time inference for object detection and distance estimation: Real-time inference ensures that the system processes and responds to data instantly, enabling quick feedback on objects and distances.
- Minimize power consumption for 8+ hours of operation on a 2000mAh battery: The system is designed to optimize power usage, ensuring the device runs for over 8 hours on a 2000mAh battery.

6. METHODOLOGY

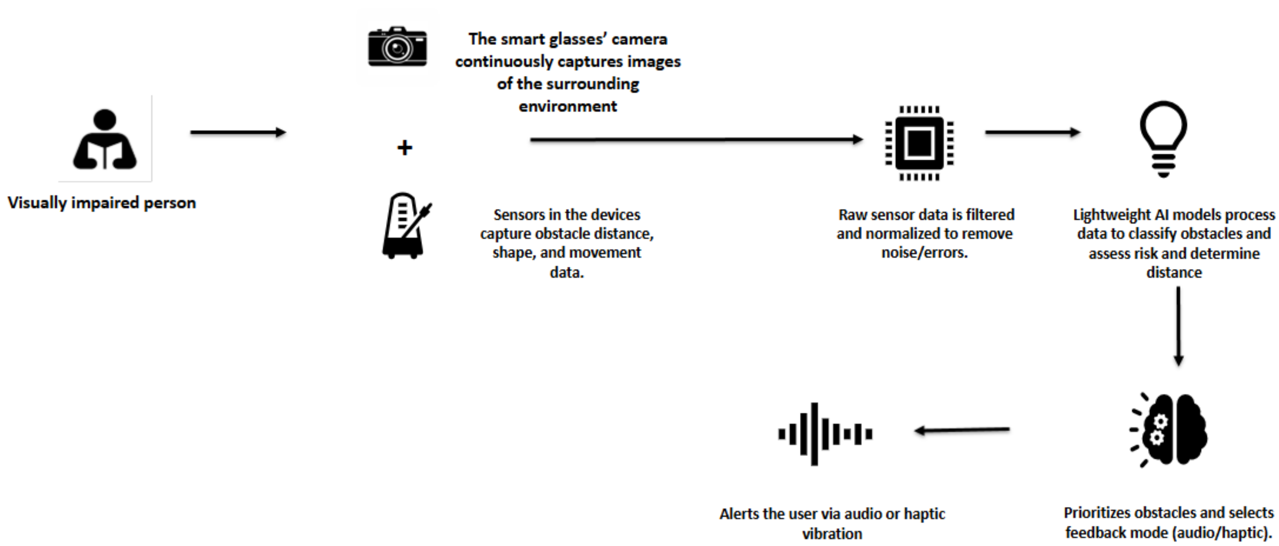
6.1. OVERALL SYSTEM DESCRIPTION

The proposed assistive system is a wearable pair of smart glasses designed to enhance environmental perception for visually impaired users. It incorporates ultrasonic sensors, a camera, and Edge AI/TinyML processing to detect obstacles, measure distances, and identify objects in real time. The system operates in four key stages:

- Ultrasonic Sensors Measure distances to obstacles using time-of-flight principles, providing proximity data within a specific range. Camera Module Captures images to be processed for object detection and recognition, helping the system understand the environment.
- Microcontroller Integration Combines data from the ultrasonic sensors and camera to form a comprehensive understanding of the surroundings. TinyML Models Process images locally to classify objects in real-time, enhancing environmental awareness for the user.
- Sensor Fusion with Filter A filter is used to merge data from different sensors, compensating for any discrepancies and improving the accuracy of distance estimation. Priority Logic The system identifies and prioritizes critical obstacles, adjusting the feedback to provide the most relevant navigation assistance.
- Voice Alerts Verbal descriptions of detected objects and their distances are delivered through a speech synthesis module, aiding in spatial awareness. Haptic Feedback Vibration motors integrated into the glasses' frame provide tactile feedback, indicating obstacle direction and proximity.
- Battery and Optimization Powered by a rechargeable battery, the system is optimized for energy efficiency through sleep modes and low-power components, ensuring long-duration operation.

This design ensures a seamless and intuitive experience for visually impaired users, combining advanced sensing, processing, and feedback mechanisms for enhanced independence and mobility.

6.2. SYSTEM DIAGRAM



7. PROJECT REQUIREMENTS

7.1. FUNCTIONAL REQUIREMENTS

- Obstacle Detection Range: Detects obstacles within a range of 2 cm to 4 meters using ultrasonic sensors, providing precise distance measurements for objects at varying distances.
- Real-Time Object Classification: Captures visual data to detect and classify objects like doors, stairs, and vehicles in real time, aiding in navigation by identifying obstacles in the user's environment.
- Distance Calculation Using Fused Data: Calculates the distance to detected objects by combining data from ultrasonic sensors and camera-based depth estimation, offering accurate and reliable measurements.
- Obstacle Classification: Classifies common indoor and outdoor obstacles, such as furniture or vehicles, enabling better understanding of the surroundings and assisting in navigation.
- Static vs Dynamic Obstacle Detection: Distinguishes between static obstacles (e.g., walls) and dynamic obstacles (e.g., moving pedestrians or vehicles), ensuring appropriate feedback is given based on the type of obstacle.
- Voice Feedback: Provides voice feedback, including distance-based alerts, using a text-to-speech module to inform the user about obstacles and their proximity in real time.
- Directional Haptic Feedback: Delivers directional haptic feedback to indicate the location of obstacles, helping the user navigate by providing tactile cues about the surroundings.
- Prioritized Alerts for Critical Obstacles: Triggers voice and haptic feedback for high-priority obstacles, like moving vehicles, ensuring the user is promptly alerted to dangerous situations.
- Basic Route Guidance: Offers basic route guidance by using preloaded maps and GPS (optional), assisting users with navigation through known environments or predefined routes.
- User-Controlled Feedback Modes: Allows users to activate or deactivate different feedback modes (voice-only, haptic-only, or combined) via a tactile button, providing customizable feedback options.
- Local Data Processing: Processes all data locally on the device without dependency on cloud services, ensuring faster response times, increased privacy, and independence from internet connectivity.

7.2. NON-FUNCTIONAL REQUIREMENTS

- Low-Latency Processing: - The system quickly processes input data, ensuring minimal delay between detecting obstacles and providing feedback. Edge AI and TinyML allow local data processing, reducing response time and eliminating cloud dependency for faster reactions.
- Accurate Distance Measurement: - Ultrasonic sensors measure distance by emitting sound waves and calculating the return time. This data, combined with camera inputs, provides precise obstacle distance, helping the user navigate safely and effectively.
- Proximity-Based Haptic Feedback: - The system provides real-time tactile feedback based on object proximity. Stronger vibrations indicate closer obstacles, while lighter vibrations show distance, helping users navigate intuitively without relying on visual cues.
- Lightweight and Comfortable Design: - The glasses are ergonomically designed to be lightweight and comfortable for extended use. Using flexible materials, they minimize strain on the head and neck, ensuring the user can wear them for long periods without discomfort.
- Privacy-Focused Data Processing: - Data is processed locally on the device to protect sensitive information, such as location and images. This minimizes privacy risks, with optional encryption and anonymization for further security.

8. BUDGET AND BUDGET JUSTIFICATION

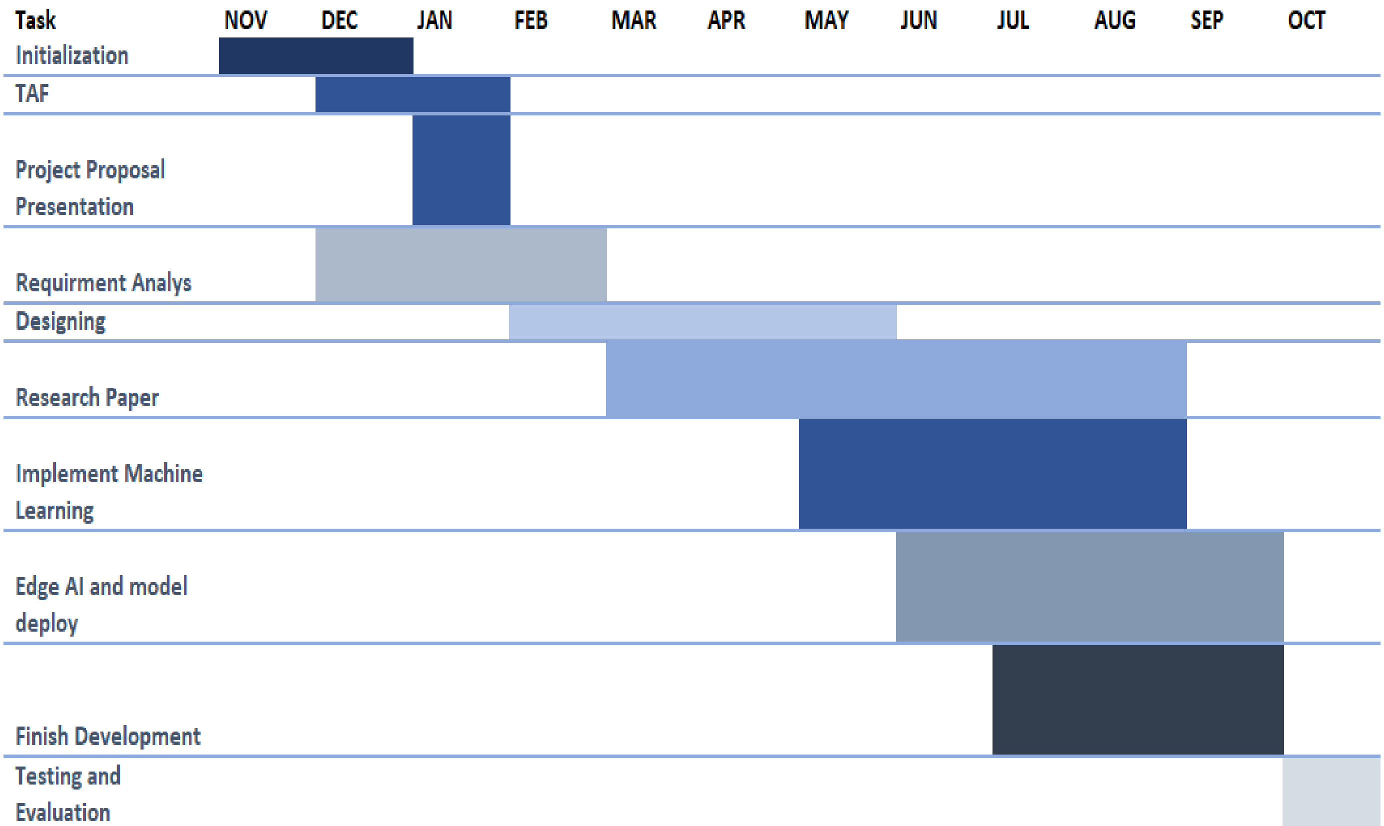
Component	**Quantity**	**Unit Price (LKR)**	**Total Cost (LKR)**
Ultrasonic Sensor (HC-SR04)	2	800	1,600
Jumper Wires	20	10	200
Breadboard	1	500	500
Switch (Push Button)	2	50	100
Earphones (Basic)	1	1,000	1,000
Safety Glasses (Frame)	1	2,000	2,000

Component	Quantity	Unit Price (LKR)	Total Cost (LKR)
Raspberry Pi Camera V2	1	4,500	4,500
Microcontroller (Arduino Nicla Vision or Raspberry Pi Pico)	1	15,000	15,000
Vibration Motors (LRA)	2	300	600
LiPo Battery (2000mAh)	1	1,500	1,500
Power Management IC (PMIC)	1	500	500
Miscellaneous (Wires, Connectors, etc.)	-	-	1,000
Total			**28,500 LKR**

Budget Justification

- Ultrasonic Sensors (HC-SR04): Essential for distance measurement; cost-effective and reliable.
- Jumper Wires and Breadboard: Necessary for prototyping and connecting components.
- Switch (Push Button): Enables user interaction (e.g., power on/off, mode switching).
- Earphones: Provides private audio feedback for user guidance.
- Safety Glasses (Frame): Acts as the wearable platform for mounting components.
- Raspberry Pi Camera V2: Captures high-quality images for object detection.
- Microcontroller: Core processing unit for running TinyML models and managing sensors.
- Vibration Motors (LRA): Delivers haptic feedback for obstacle direction and proximity.
- LiPo Battery and PMIC: Ensures portability and efficient power management.
- Miscellaneous: Covers additional wiring and unforeseen prototyping expenses.

9. GANTT CHART



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