THE UNIVERSITY OF QUEENSLAND

AUSTRALIA

Sensing the world using EM signals: using radar to gain better situational awareness

PROJECT PROPORSAL

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Content

1. Introduction

Electric scooters (e-scooters) are becoming increasingly popular due to their convenience and environmental benefits. However, their design has certain safety risks. Features like small wheel size, lack of suspension, and high center of gravity make them unstable and more prone to accidents, especially on uneven surfaces or when encountering unexpected obstacles, And because the scooter power transmission is more direct, it has the characteristics of rapid acceleration, which is a great challenge for its braking system[1]. These risks have raised public concern, especially since riders often move at high speeds or enter pedestrian areas, causing frequent near collisions and injuries[2]. Traditional campus safety measures like signs, restrictions, or CCTV cameras have limitations: cameras may fail in poor lighting or bad weather and may raise privacy concerns, while full bans limit mobility[3]. Therefore, there is a need for an automated, privacy-friendly monitoring system that can accurately detect and classify moving entities (pedestrians and e-scooter riders), analyze their posture and behavior (e.g., walking, running, riding, or falling), and reliably track them in real-time. Such a system could provide proactive alerts and data-driven safety responses on campus.

Feature	Electric Scooters	Electric Bikes
Wheel Diameter	Typically 8-10 inches	Typically 26-29 inches
Impact on Stability	Smaller wheels lead to reduced stability, especially on uneven surfaces	Larger wheels enhance stability, better at handling bumps and potholes

Figure 1 The difference of Features[4]

1.1 Research Problem

This proposal addresses the problem of safely integrating e-scooters with pedestrian traffic on campus. The core challenge is to develop a sensor system that can detect both pedestrians and e-scooters with high accuracy under diverse conditions, distinguishing between the two and analyzing their movement behaviors. Millimeter-wave (mmWave) radar is proposed as the primary sensing technology due to its robustness to lighting and weather and its ability to measure motion directly via Doppler shifts.[5].

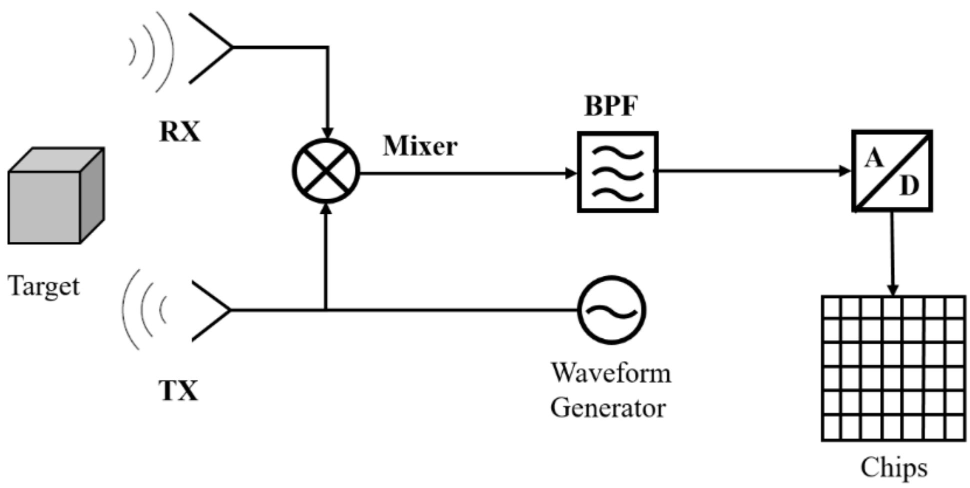

Figure 2 FMCW radar system block system[5]

1.2 Research Objectives

The project has the following goals:

- **Design** a mmWave radar-based monitoring system for campus walkways that operates in real time and provides privacy-preserving detection of both pedestrians and e-scooter riders.
- **Develop** algorithms for accurate detection and classification of human vs. e-scooter targets from the radar signals, achieving high recognition accuracy with minimal false alarms. This includes analyzing micro-Doppler effects generated by body or scooter movements[6].
- **Analyze** radar micro-Doppler signatures to distinguish target behaviors and postures – for example, differentiate normal walking/riding from running or sudden falls – as an indicator of safety risks.
- **Implement** robust multi-target tracking to continuously monitor multiple moving subjects and maintain their identities over time, even if they momentarily occlude each other or move in crowds[7].

By achieving these objectives, the research aims to create an intelligent monitoring system that enhances campus safety by detecting potential incidents early and provides valuable data to assist campus planners in risk assessment.

2. Background and Technology

2.1 mmWave Radar Technology

Millimeter-wave (mmWave) radars, operating between 24 and 77 GHz, send out high-frequency electromagnetic waves to detect objects by analyzing reflected signals. These radars use Frequency-Modulated Continuous Wave (FMCW) signals, known as chirps, to determine both the distance to objects—by measuring the time it takes for signals to return—and their velocity, through the Doppler effect. Multiple antennas enable the radar to identify the angle or direction of detected objects. Due to their short wavelengths of a few millimeters, mmWave radars offer high accuracy in measuring distances and can detect even very small movements.

In our project, I will use the Texas Instruments AWR1843 radar sensor, which operates at 77 GHz. This sensor includes three transmitters and four receivers on a single chip and provides a chirp bandwidth of up to 4 GHz, allowing very precise measurements. The AWR1843 sensor also incorporates built-in digital signal processing (DSP) hardware and an FFT accelerator, along with a microcontroller for real-time data processing directly on the device[8].

Compared to optical cameras, mmWave radars are not affected by lighting conditions and can function effectively through fog or rain, making them ideal for continuous outdoor monitoring in any weather or time of day. Importantly, radars detect only motion and distance, without capturing details of identity or appearance, ensuring privacy is maintained. These features highlight the suitability of mmWave radar technology for enhancing campus safety in our application.

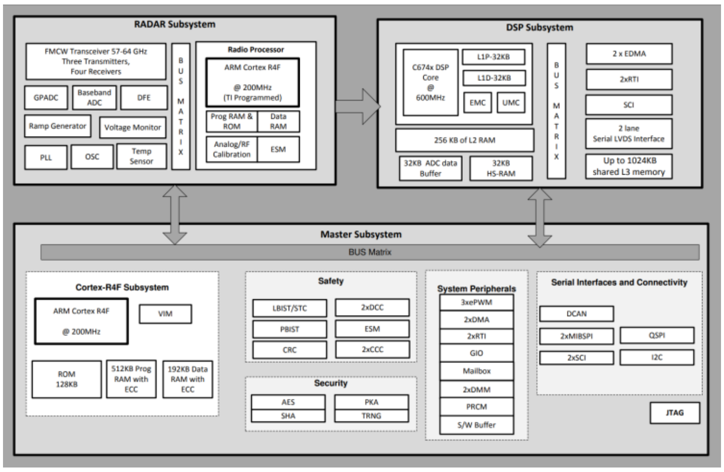

Figure 3 The 1843 block diagram[8]

2.2 Micro-Doppler Signatures

Beyond detecting basic movements, radar technology can identify subtle frequency variations known as micro-Doppler effects. These variations occur due to internal motions within objects, such as the swinging of a person's limbs or the rotation of a scooter's wheels. These micro-Doppler patterns serve as unique signatures, allowing the radar to distinguish between different objects or actions. For example, a pedestrian generates a regular Doppler pattern through arm and leg movements, while someone riding an e-scooter shows a different frequency pattern due to continuous wheel rotation and limited limb motion. Previous research, illustrated in Figure 4, shows how the micro-Doppler signature of a pedestrian changes with the height of the radar[5].

In the application, these signatures will help us determine whether a detected moving object is an e-scooter, which has specific wheel-related Doppler characteristics, or a pedestrian. This understanding will assist us in developing algorithms capable of classifying patterns such as walking versus riding a scooter. Researchers have previously shown that micro-Doppler patterns at 77 GHz can effectively differentiate between pedestrians and bicycles, and I'm extending this capability to include e-scooters[9].

2.3 GP-GPU Acceleration for Radar Signal Processing

To achieve real-time performance, our system will use GPU acceleration for intensive radar data processing tasks. Radar sensors generate substantial amounts of data, including high chirp rates and dense point clouds. Processing these data with methods such as fast Fourier transforms (FFTs), filtering, and object tracking can be challenging for CPUs alone. GPUs, however, excel at parallel computing tasks such as FFTs and linear algebra operations[10].

Previous studies indicate that transferring radar data processing to a CUDA-enabled GPU significantly boosts performance, allowing real-time processing speeds that CPUs typically cannot achieve. In this project, data collected from the AWR1843 radar sensor will be sent directly to a GPU-enabled computing device, such as a laptop with an NVIDIA GPU[11]. The GPU will manage demanding processes like range and Doppler FFT calculations, clustering detected points, and possibly running neural network models for classification. Utilizing GPU parallel processing helps prevent delays in data handling and ensures the system can promptly detect and track targets, crucial for effective live monitoring.

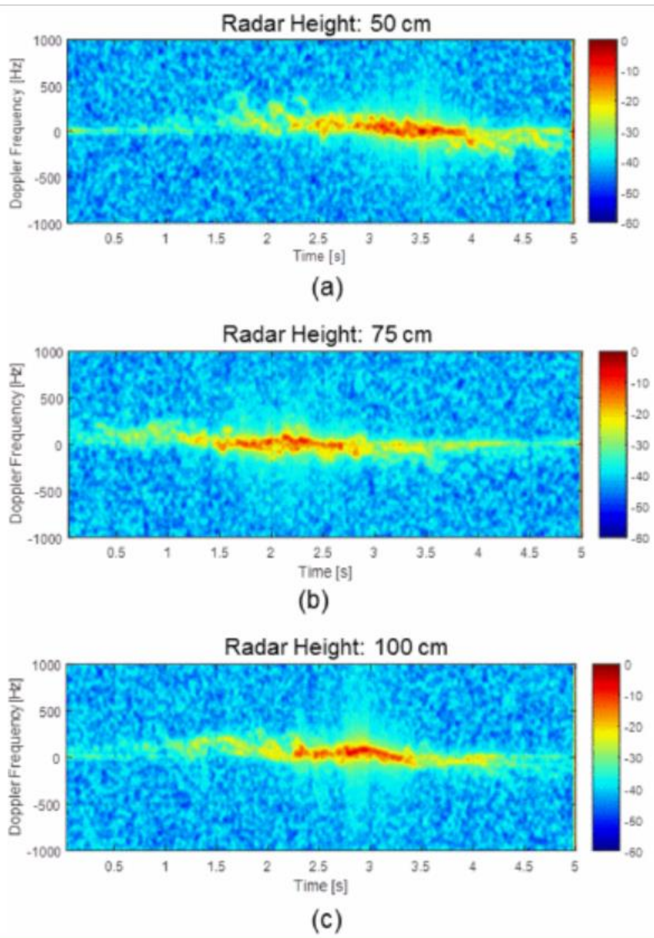

Figure 4 micro-doppler responses for radar heights of (a) 50 cm, (b) 75 cm, (c) and 100 cm of the pedestrian walking arcoss the radar.[9]

3. Literature Review

3.1 Active and Passive Radar Approaches

Previous research has examined both active mmWave radar systems and passive radar techniques to track human movements. Active mmWave radar is widely established in automotive safety applications; for instance, modern cars utilize 77 GHz FMCW radar technology to detect pedestrians and cyclists, helping to prevent collisions. This successful application supports the effectiveness of mmWave radar for identifying vulnerable road users.

On the other hand, passive radar approaches have also been studied for sensing human activities. For example, research by Li et al. showed that passive radar using ambient 2.4 GHz Wi-Fi signals could detect the distance and speed of a running person outdoors. Recent reviews indicate increasing interest in passive radar systems for recognizing activities. Passive radar systems offer advantages such as being unobtrusive and requiring minimal hardware by utilizing existing signals[12]. However, these systems usually produce lower-quality signals and involve complex data processing techniques. So far, passive radar has not been tested for distinguishing e-scooter riders. So mmWave radar continues to be the preferred method for reliable detection in our project.

3.2 Pedestrian and Micro-Mobility Detection

Radar technology for detecting pedestrians and monitoring traffic has expanded from vehicle-based systems to broader uses in smart cities and campus environments. Stationary radar sensors installed at intersections can accurately count pedestrians and vehicles in real-time, effectively covering larger areas than traditional methods like cameras or inductive loops. These studies emphasize radar's key benefits, including its reliability under various lighting and weather conditions and minimal need for extensive infrastructure, making it particularly suitable for campus safety applications.

Regarding micro-mobility, previous research has predominantly depended on camera-based detection methods. However, as noted by Gilroy et al., image-based detection systems can mistakenly classify e-scooter riders as pedestrians because they look similar, despite their distinct motion characteristics[13]. This limitation of visual detection methods highlights the potential advantage of radar, which uses motion-based information, to more accurately differentiate between pedestrians and e-scooter users.

3.3 Radar Classification of Vulnerable Road Users

Recent studies have begun using mmWave radar technology to classify various moving individuals or objects. For example, Chen et al. successfully developed a micro-Doppler-based method using 77 GHz radar to distinguish between pedestrians and cyclists, demonstrating high accuracy in controlled environments[4]. Similarly, Belgiovane and Chen (2017) examined radar returns at 77 GHz and found distinct micro-Doppler signatures differentiating pedestrians from bicycles[9]. Their research, involving over 500 examples of diverse road users, revealed unique frequency patterns resulting from limb movements and wheel rotations. This suggests that radar could similarly identify e-scooter riders based on their micro-Doppler features.

These findings support the potential of radar signatures for effectively classifying different moving entities. However, previous research mainly emphasized accuracy in controlled experimental conditions. There are still important gaps in combining classification with real-time tracking of multiple targets, especially for distinguishing e-scooter riders from pedestrians in realistic campus scenarios. To date, no system specifically addresses the challenge of identifying and tracking e-scooter riders alongside pedestrians for safety management purposes. Our research aims to fill this gap by leveraging the demonstrated capabilities of mmWave radar detection and micro-Doppler analysis, further developing a real-time tracking and alert system designed for managing pedestrian-scooter interactions on campus.

4. Methodology

The proposed solution integrates a mmWave radar sensor with a data processing pipeline that covers data collection, signal processing, object classification, and multi-target tracking. The overall workflow is illustrated below.

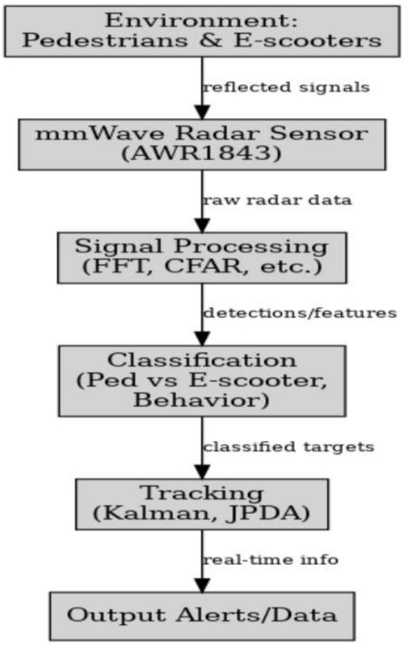

Figure 5 Block diagram of the proposed measurement setup and data processing pipeline.

4.1 Sensor Setup and Data Collection

I will mount the TI AWR1843 mmWave radar at a strategic campus location (e.g. beside a busy pathway or intersection). The radar will be angled to cover the flow of pedestrian and e-scooter traffic within a range of roughly 30 m. I will collect extensive radar data under diverse conditions – e.g. students walking alone, groups of pedestrians, individuals riding e-scooters at varying speeds, during different times of day and weather conditions. Alongside the radar recordings, I will log contextual information to aid labeling (for example, noting down ground-truth observations or using a synchronized camera solely for annotation purposes). All raw sensor data will be stored securely for offline analysis and for training the classification algorithms.

4.2 Signal Processing and Detection

Raw radar ADC signals will undergo processing through a standard FMCW radar signal pathway to identify moving targets. This process involves applying range FFT and Doppler

FFT techniques to the chirp data, generating a range-Doppler map for every frame, with a typical radar frame rate between 10 and 20 frames per second. From these maps, I will use a Constant False Alarm Rate (CFAR) detector to highlight important reflections that correspond to actual objects. To reduce interference from stationary items such as lamp posts or walls, clutter removal methods like static background subtraction or built-in moving target indication will be applied.

The final output from each radar frame will consist of detected points, each having characteristics such as range, angle, radial velocity, and radar cross-section (RCS intensity). Together, these points form a real-time "point cloud," showing moving objects within the monitored area. The complete signal processing chain will be optimized using GPU acceleration to provide detection results rapidly, ensuring minimal delay after capturing each radar frame.

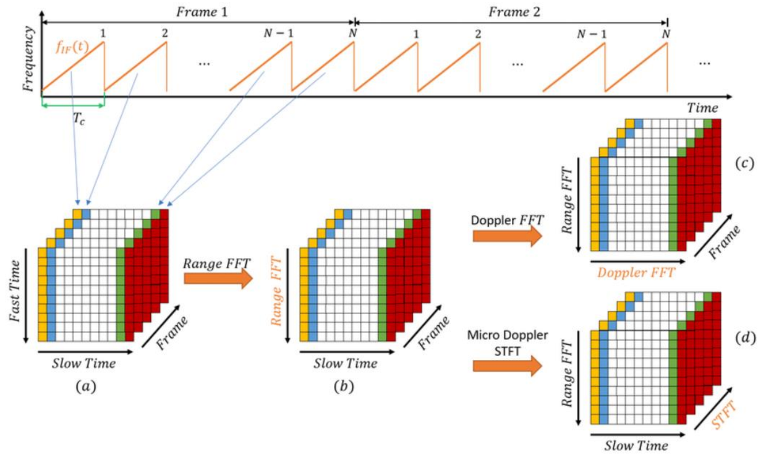

Figure 6 FMCW processing flow[17]

4.3 Classification

Next, each detection or group of detected points is classified to identify whether it represents a pedestrian or an e-scooter. I will investigate both simple rule-based methods and machine learning techniques for this classification task. Initially, straightforward criteria might be used, such as recognizing an e-scooter based on consistently higher radial speeds and larger radar cross-section (RCS) values compared to typical human figures[15]. However, for greater accuracy, I plan to create a machine learning classifier trained on our labeled dataset from recorded radar data. Suitable models could include Support Vector Machines or Random Forests, trained using physical characteristics such as average speed, speed variations, RCS, and possibly the distribution of the point cloud.

I will also explore deep learning approaches, such as training a small neural network to directly identify the type of object from Doppler time-frequency signatures. Additionally, the system will assess the behavioral status of each detected target. For pedestrians, Doppler signals can indicate whether the person is walking normally, running, or stationary. For e-scooters, specific Doppler patterns, such as sudden decreases in signal accompanied by abrupt range changes, could signal falls or sudden stops.

Each detected target will therefore be assigned both a category (pedestrian or e-scooter) and an activity status (regular movement or unusual event). The classification module will be fine-tuned and verified using labels, aiming initially for over 70% accuracy in differentiating these categories under various conditions.

4.4 Multi-Target Tracking

To continuously observe the scene, I will use a multi-target tracking algorithm that connects detections across consecutive frames. I intend to employ a tracking method such as a Kalman filter for each target, along with data association techniques to match new detections to existing tracks. Given the potential for multiple pedestrians and scooters to appear simultaneously, I may apply methods like Global Nearest Neighbor or Joint Probabilistic Data Association (JPDA) to manage uncertain associations. Each tracked object will receive a unique identifier, and the system will continuously estimate its position, speed, and trajectory[16].

If a target temporarily disappears—for instance, due to brief obstructions or radar limitations—the tracker will predict its position using its motion history, helping to maintain track continuity during short detection gaps. When the object reappears, the system will resume tracking seamlessly. The tracking module will produce real-time data of all moving targets within radar coverage, which can trigger alerts, such as potential collisions between pedestrians and scooters or detected fall incidents.

I will assess tracking performance using metrics like track consistency and the stability of object identifiers in our experimental scenarios. Integrating tracking with the classification process will allow our system not only to identify objects momentarily but also monitor their ongoing behavior and movements, significantly enhancing situational awareness and improving campus safety.

5. Research Plan and Timeline

This 12-month project includes several phases:

- **Phase 1 – Literature Review and Planning (March):** Perform an in-depth review of related work on radar-based detection, classification, and tracking of pedestrians and micro-mobility. Identify suitable hardware and software tools. Refine research questions and metrics for success.

  Deliverables: Literature review, system requirements.

- **Phase 2 – System Design and Hardware Setup (April):** Acquire the mmWave radar sensor and any auxiliary equipment. Design the experiment setup and install the sensor on campus at the chosen location. Develop initial data logging software.

  Deliverables: Radar setup and test, initial dataset.

- **Phase 3 – Data Collection and Analysis (May–June):** Collect a comprehensive dataset covering various scenarios (multiple sessions at different times of day and conditions). Begin annotating the data (labeling segments where a person or scooter is present, noting ground truth classes and events). Conduct basic analysis of radar signatures for pedestrians and e-scooters to inform feature design.

  Deliverables: Annotated dataset, analysis report.

- **Phase 4 – Detection and Classification Algorithms (July):** Implement the signal processing pipeline for detection (range-Doppler processing and CFAR). Develop and train the classification model using the collected data (split into training and testing sets). Iterate model design (try CNN spectrogram-based vs. feature-based, etc.) to achieve target accuracy (e.g., >70% classification correctness in test scenarios)

  Deliverables: Detection algorithm, trained model (target >70% accuracy).

- **Phase 5 – Behavior Analysis and Tracking (Aug–Sept):** In parallel with Phase 4, develop methods for posture/behavior recognition (e.g., add activity labels to training data and train the model to output these, or create a separate classifier for behaviors). Also implement the multi-target tracking module and integrate it with detection (so that each frame's detections update the tracker). Test the tracking on sequences from our data, refine gating and data association parameters to maintain stable tracks.

  Deliverables: Integrated tracking + classification software.

- **Phase 6 – Debug and Optimization (Oct):** Integrate all components into a real-time prototype. Run end-to-end tests on campus (with live radar streaming) to assess performance in a real deployment scenario. Any issues (e.g., latency, false alarms) are identified and mitigated (through code optimization or parameter tuning).

  Deliverables: Working prototype.

- **Phase 7 – Evaluation and Refinement (Oct):** Rigorously evaluate the system against the objectives. This includes measuring detection range, classification accuracy (ped vs scooter, and correct posture recognition), tracking continuity (how long targets are kept without ID switches or losses), and system response time. I will also test edge cases (multiple scooters and many pedestrians, heavy rain if possible using water spray to simulate, etc.) to probe limitations. Based on results, refine the algorithms or models in any weak areas.

  Deliverables: Evaluation report.

- **Phase 8 – Final Report and Presentation (Oct–Nov):** Compile a comprehensive project report (thesis or proposal final report) in IEEE format, documenting the design, methodology, results, and discussion. Also prepare a presentation for stakeholders (e.g., campus safety office) to demonstrate the system's capabilities and discuss implementation pathways.

  Deliverables: Final paper, slides.

Some phases overlap (for example, Phase 5 overlaps with late Phase 4) to expedite development – while classification is being fine-tuned, tracking can be developed concurrently. This parallel effort is indicated in the Gantt chart. Regular milestones (monthly meetings or internal demos) will ensure the project stays on schedule. By the end of the timeline, I expect to have a validated prototype and all research questions addressed.

6. Ethics and Risk Analysis

6.1 Ethical Considerations

The project involves monitoring people on campus. While mmWave radar doesn't record images or identities, it can capture movement. I will fully follow privacy and ethics rules. Radar will be used openly, only for safety. Data will be anonymized and stored securely. Volunteers will give informed consent[17].

The system will be privacy-friendly by design. It may generate alerts but won't store raw data long term, except for summarized data needed by safety staff. This prevents misuse or accidental surveillance[18].

6.2 Risk Analysis

- **Detection Accuracy:** Radar might incorrectly identify targets—for example, merging two pedestrians into one or mistaking an e-scooter rider for a larger vehicle. To reduce this risk, I will refine detection algorithms, improve resolution and CFAR settings, and include additional features like micro-Doppler signatures. Extensive testing will further optimize classifier thresholds and reduce errors.

- **Tracking Loss:** Rapidly moving e-scooters might quickly exit radar coverage, or targets could be temporarily obscured. I will mitigate this by possibly overlapping coverage with multiple radars or enhancing the tracker's prediction capability (such as employing advanced Kalman filters). Proper sensor placement will also minimize occlusions.

- **Hardware Limitations:** The radar or processing hardware might struggle with crowded scenes or high data volumes. To address this, I will optimize computations using GPU acceleration, adjust radar frame rates, coverage areas, or implement advanced algorithms for efficiency. If necessary, I will upgrade hardware, having allowed buffer time for this.

- **Schedule Risk:** Data collection and testing could be delayed by poor weather or limited campus access. Our project plan includes flexibility to shift tasks, perform offline analyses, and use multiple data collection periods. Alternative locations or controlled experiments will also be considered if needed.

- **Operation Risk:** Despite the radar's safe, low-power signals, regulatory compliance and community concerns must be addressed. Equipment will be securely installed, labeled clearly, and compliant with local regulations. Privacy will be strictly maintained by recording only anonymous movement data.

7. Expected Outcomes

By the end of the project, I aim to achieve the following main outcomes:

- **Prototype System**: I will develop a working prototype using mmWave radar technology for monitoring purposes on campus. This system will accurately detect, classify, and track pedestrians and e-scooter users in real-time. It will include both the hardware setup and the complete software solution covering signal processing, machine learning classification, and tracking, all demonstrated in realistic campus conditions
- **Algorithms and Dataset:** I will deliver proven algorithms for classifying targets and tracking multiple objects simultaneously. This includes the trained classification models, clearly documented with performance metrics such as accuracy rates above 70% and confusion matrices from test data. Additionally, I will compile a labeled dataset containing radar data, including range-Doppler maps and micro-Doppler signatures, along with ground-truth labels. This dataset will support future research efforts and may be shared with the broader research community in an anonymized format.
- **Documentation and Report:** Detailed documentation outlining the system's design and experimental results will be provided, accompanied by a comprehensive final report or thesis. This documentation will describe our methodology, analyze achieved results—including detection and classification accuracy—and showcase examples of alerts triggered by the system in various situations. It will also offer practical recommendations for scaling up and implementing the system effectively. Such detailed reporting will help stakeholders and future researchers understand the system's capabilities, limitations, and potential for further development or deployment.

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