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Project Report On

"ResQNow: AI-AR First Aid & Emergency App"

Submitted in partial fulfillment of the requirements for the award of the Degree of

Bachelor of Engineering

in

CSE (IoT & Cyber Security including Blockchain Technology)

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CERTIFICATE

This is to certify that the project report entitled **"ResQNow: AI-AR First Aid & Emergency App"** submitted by **A P SAROON (1BI22IC001), MEDHA BHAT (1BI22IC038), SUFAILA T S (1BI22IC057) and PRANAVA N A (1BI23IC405)** to the Visvesvaraya Technological University, Belagavi, in partial fulfillment for the award of the degree of **B.E. in Computer Science and Engineering (IoT & Cyber Security including Blockchain Technology)** is a *bonafide* record of project work carried out by them under our supervision. The contents of this report, in full or in parts, have not been submitted to any other Institution or University for the award of any degree.

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DECLARATION

We declare that this project report titled **"ResQNow: AI-AR First Aid & Emergency App"** submitted in partial fulfillment of the degree of **B.E. in Computer Science and Engineering(IoT & Cyber Security including Blockchain Technology)** is a record of original work carried out by us under the supervision of **Dr. ANUPAMA K C**, and has not formed the basis for the award of any other degree, in this or any other Institution or University. In keeping with the ethical practice in reporting scientific information, due acknowledgements have been made wherever the findings of others have been cited.

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Abstract

Timely response during life-threatening emergencies is often hindered by delayed reporting, lack of bystander guidance, limited situational awareness, and complete dependence on internet connectivity in existing emergency support systems. To address these challenges, this project proposes **ResQNow**, an AI- and AR-powered emergency response and first-aid assistance system designed for both online and offline operation. The system integrates a Flutter-based mobile application with a Python (FastAPI) backend and Firebase services to enable rapid SOS activation, continuous GPS tracking, secure user authentication, and coordinated responder acknowledgment. Emergency severity is determined using a dual-mode intelligence framework combining cloud-based conversational AI with an offline rule-based classifier. For immediate on-site assistance, ARCore-enabled visual guidance supports critical procedures such as CPR and AED usage. Encrypted Bluetooth Low Energy (BLE) communication ensures SOS propagation in low-connectivity environments. Experimental results demonstrate SOS dispatch times of 2–3 seconds, AR initialization latency below 1.5 seconds, BLE relay reliability above 90%, and emergency classification accuracy of approximately 89%, validating the system's efficiency and resilience.

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Chapter 1

INTRODUCTION

This chapter introduces the background, motivation, and problem context of the proposed ResQNow: AI–AR First Aid & Emergency App. It highlights the challenges associated with existing emergency response mechanisms, outlines the objectives of the project, defines the problem scope, and presents the proposed solution. The chapter establishes the foundational need for an intelligent, technology-driven emergency response system capable of assisting users during critical situations.

1.1 Background and Overview

Medical emergencies demand immediate intervention, as delays during the initial minutes can significantly increase mortality and long-term complications. In many real-world situations, professional medical assistance is not instantly available, placing untrained bystanders in a critical position to provide first aid. This highlights the need for intelligent, technology-driven emergency response systems that can support timely and effective intervention.

1.1.1 The Critical Nature of Emergency Response

Medical emergencies such as cardiac arrest, severe bleeding, burns, road accidents, and sudden health collapse require immediate intervention within the first few minutes to prevent fatal outcomes. In many real-world scenarios, professional medical assistance is not instantly available, and the responsibility of providing initial aid often falls on nearby bystanders. These individuals are typically untrained, uncertain about correct first-aid procedures, and hesitant to intervene due to fear of causing further harm.

The concept of the "golden hour" in emergency medicine emphasizes that the first 60 minutes following a traumatic injury are the most critical for survival. However, research indicates that even shorter time windows, often referred to as the "platinum ten minutes", are decisive in cases of cardiac arrest, severe hemorrhage, or respiratory failure. During these crucial moments, the availability of immediate assistance and the

quality of initial intervention directly determine patient outcomes. Statistics reveal that survival rates for cardiac arrest victims drop by approximately 10% with each passing minute without CPR or defibrillation. Similarly, uncontrolled bleeding can lead to irreversible shock within minutes, and improper handling of burn injuries can significantly worsen tissue damage and infection risk.

Despite the clear importance of rapid response, the reality in most emergency situations is far from ideal. Ambulance response times vary significantly across urban and rural regions, with average arrival times ranging from 5 to 15 minutes in cities and extending beyond 30 minutes in remote areas. In densely populated urban centers, traffic congestion, limited road access, and communication delays further impede emergency vehicle movement. In rural and disaster-affected regions, the scarcity of medical infrastructure, inadequate transportation networks, and poor communication systems create additional barriers to timely professional intervention.

In such scenarios, the presence of trained bystanders capable of administering basic life support can substantially improve survival rates. However, formal first-aid training is not widespread among the general population. Surveys indicate that fewer than 30% of adults have received any form of first-aid or CPR training, and even among those trained, confidence levels remain low due to lack of practice and fear of legal consequences. This reluctance to act is compounded by the absence of clear, real-time guidance during actual emergencies, where stress, panic, and uncertainty dominate decision-making.

1.1.2 Limitations of Conventional Emergency Systems

Conventional emergency response systems rely primarily on emergency helpline calls and manual communication. Such mechanisms are highly dependent on stable network connectivity, provide limited situational awareness, and fail to deliver real-time, on-site procedural guidance. As a result, valuable time is lost during the critical early stages of an emergency, significantly reducing survival probability. Traditional helpline systems require the caller to verbally describe the situation, often under extreme stress, leading to incomplete or inaccurate information being

conveyed to dispatchers. Furthermore, these systems do not provide immediate assistance to the caller or bystanders, leaving them without actionable instructions until professional help arrives.

The dependency on voice-based communication introduces several inherent limitations. During high-stress situations, individuals often struggle to articulate symptoms accurately, leading to misclassification of emergency severity. Language barriers, hearing impairments, and environmental noise further complicate effective communication. Additionally, traditional systems lack the capability to capture visual or contextual information that could aid in severity assessment and resource allocation. The passive nature of these systems means that bystanders remain idle while waiting for professional help, missing critical opportunities to provide life-saving interventions.

Network connectivity represents another fundamental constraint of existing emergency response mechanisms. In disaster scenarios, natural calamities, or regions with poor telecommunications infrastructure, cellular networks frequently become congested or completely unavailable. During such events, the inability to place emergency calls or transmit location information renders conventional systems ineffective precisely when they are needed most. This connectivity dependency creates a critical vulnerability that can result in delayed or failed emergency responses.

1.1.3 Technological Enablers for Modern Emergency Response

The advent of smartphones and mobile computing has introduced new possibilities for emergency response enhancement. Modern smartphones are equipped with powerful processors, high-resolution cameras, GPS receivers, various sensors including accelerometers and gyroscopes, and multiple communication interfaces such as cellular networks, Wi-Fi, and Bluetooth. These capabilities position smartphones as ideal platforms for intelligent emergency response systems that can detect, classify, and respond to emergencies with minimal human intervention.

Artificial intelligence has emerged as a transformative technology across healthcare domains, including emergency triage, diagnostic assistance, and predictive analytics. Machine learning models trained on large datasets of emergency case reports can identify patterns and classify emergency severity with high accuracy. Natural language processing techniques enable conversational interfaces that can gather critical information from users quickly and efficiently. Computer vision algorithms can analyze images and video feeds to detect visible injuries or hazards. When integrated into mobile emergency response systems, AI can provide rapid situational assessment, prioritize alerts based on severity, and deliver personalized guidance tailored to specific emergency types.

Augmented reality represents another breakthrough technology with significant potential for emergency response applications. AR overlays digital information onto the real-world view captured by a device's camera, creating an immersive and intuitive interface for procedural guidance. In the context of first aid, AR can visually demonstrate correct hand placement for chest compressions, highlight anatomical landmarks for tourniquet application, and provide step-by-step instructions for using automated external defibrillators. Unlike traditional text or video-based guidance, AR-based instructions are contextualized to the user's immediate environment, reducing cognitive load and improving comprehension under high-stress conditions. Research in AR-assisted medical training has demonstrated significant improvements in procedure retention and execution accuracy compared to conventional instruction methods.

Global positioning systems have become ubiquitous in modern mobile devices, enabling precise location tracking and navigation. In emergency scenarios, GPS data can be used to identify the exact location of incidents, guide responders to the scene, and provide situational context to emergency services. Real-time location sharing allows family members and emergency contacts to track the status of their loved ones during critical situations. Location-based alerts can notify nearby trained responders or medical volunteers, creating a distributed emergency response network that operates independently of centralized infrastructure. The accuracy of modern GPS systems, often within a few meters, enables responders to locate victims even in complex urban environments or unfamiliar terrain.

1.1.4 The Integration Gap and Resilience Challenge

Despite the availability of these advanced technologies, existing emergency support applications remain largely limited in scope and functionality. Most current solutions focus on a single aspect of emergency response, such as location sharing, emergency dialing, or static first-aid reference materials. Few systems integrate multiple technologies into a cohesive platform capable of intelligent emergency detection, guided intervention, and resilient communication. Furthermore, nearly all existing solutions depend entirely on continuous internet connectivity, rendering them ineffective in areas with poor network coverage or during large-scale disasters when cellular infrastructure may be compromised.

Bluetooth Low Energy technology offers a promising solution to the connectivity challenge. BLE enables short-range wireless communication between devices with minimal power consumption. In emergency contexts, BLE can be used to create ad-hoc mesh networks where SOS alerts are relayed from device to device until reaching one with internet connectivity. This offline relay mechanism ensures that emergency notifications can propagate even in network-constrained environments, significantly improving system reliability and coverage. The low power consumption of BLE makes it particularly suitable for emergency applications where device battery life is critical.

The integration of AI, AR, GPS, and BLE technologies into a unified emergency response platform represents a significant advancement over existing approaches. Such a system can automatically detect and classify emergencies, provide immersive visual guidance for life-saving procedures, accurately track and share location information, and maintain operational continuity even without internet access. By empowering ordinary individuals with intelligent tools and real-time guidance, this integrated approach has the potential to dramatically improve emergency response outcomes and save lives.

The development of ResQNow addresses these challenges by bringing together cutting-edge technologies in a practical, user-centered mobile application. The system is designed to be intuitive enough for untrained users to operate under stress, reliable enough to function in diverse environmental conditions, and intelligent

enough to adapt to varying emergency scenarios. Through careful integration of AI-driven classification, AR-based procedural guidance, GPS-enabled location tracking, and BLE-supported offline communication, ResQNow aims to transform how individuals respond to medical emergencies before professional help arrives.

1.2 Motivation

Despite the widespread availability of smartphones, existing emergency-support solutions remain largely reactive and limited in functionality. Victims or witnesses are expected to manually describe emergency situations, wait passively for assistance, and depend entirely on continuous internet connectivity. This leads to delayed responses, lack of actionable guidance, and system failure in rural areas, disaster zones, or connectivity-constrained environments.

Bystanders frequently avoid providing assistance due to uncertainty regarding life-saving procedures such as cardiopulmonary resuscitation (CPR), bleeding control, or burn management. Even when willing to help, the absence of clear visual and contextual guidance results in ineffective or incorrect intervention. Legal concerns and fear of liability further discourage well-intentioned individuals from providing aid in life-threatening situations.

The motivation behind ResQNow is to bridge this critical gap by enabling immediate, intelligent, and guided emergency response at the user level. By integrating AI-driven emergency classification, immersive AR-based first-aid guidance, and offline SOS propagation using Bluetooth Low Energy (BLE), the system empowers individuals to act confidently and effectively during emergencies, thereby improving survival outcomes. In addition, the system emphasizes resilience by ensuring continued operation during network outages and infrastructure disruptions common in real-world emergency scenarios. Severity-aware alert prioritization further reduces response delays by directing attention to critical cases. This approach enhances situational awareness for responders while reducing cognitive load on distressed users. Consequently, the system supports faster, more coordinated, and life-saving interventions before professional help arrives.

1.3 Objectives of the Project

The primary objectives of the ResQNow project are to:

- Design a mobile-based emergency response system that enables rapid SOS activation with minimal user interaction.
- Implement AI-based emergency classification for real-time identification of emergency type and severity.
- Provide AR-based visual first-aid guidance to assist untrained bystanders in performing life-saving procedures.
- Enable continuous GPS-based location tracking and alert dissemination to emergency contacts and responders.
- Ensure reliable SOS delivery during internet unavailability using BLE-based offline relay communication.
- Maintain data security and user privacy through authenticated access and encrypted communication.
- Evaluate system effectiveness using measurable metrics such as response latency, reliability, and classification accuracy.

1.4 Problem Statement

In many emergency situations, the absence of immediate professional medical assistance, combined with limited first-aid knowledge among bystanders, results in preventable loss of life. Existing emergency response systems primarily rely on voice-based communication and manual reporting, providing no real-time procedural guidance and minimal intelligence for assessing emergency type and severity. Moreover, these systems are highly dependent on continuous network connectivity, rendering them ineffective in rural regions, disaster-affected areas, and crowded environments where communication infrastructure is unreliable.

Addressing this issue is critically important because the initial minutes following an emergency incident play a decisive role in patient survival. Delayed response, misinterpretation of emergency severity, and incorrect or absent first-aid intervention significantly increase fatality risk. In the absence of accessible, real-time guidance, even willing bystanders often remain passive due to fear, uncertainty, or lack of confidence, resulting in missed opportunities for life-saving intervention.

The proposed ResQNow system addresses this problem by providing an intelligent mobile-based emergency response platform that integrates AI-driven emergency severity classification, immersive AR-guided first-aid assistance, and resilient SOS communication through BLE-based offline relay networking. By reducing response latency, enabling guided intervention for untrained bystanders, and ensuring reliable alert delivery under poor connectivity conditions, the system aims to improve emergency coordination and survival outcomes while remaining feasible within academic and resource constraints.

1.5 Proposed Solution Overview

ResQNow adopts a layered client–server architecture centered around a Flutter-based mobile application and a FastAPI-powered backend to address the limitations of conventional emergency response systems. The mobile application enables rapid SOS activation through manual or voice-based triggers and captures contextual data such as user input and GPS location, which is securely transmitted to the backend for AI-based emergency type and severity analysis, enabling timely and informed response initiation.

For immediate bystander assistance, the application activates augmented reality (AR) overlays aligned with the real-world camera view, visually guiding correct hand placement and procedural steps for CPR, AED usage, and basic first-aid actions. In scenarios where internet connectivity is unavailable, encrypted SOS packets are forwarded via Bluetooth Low Energy (BLE) to nearby ResQNow-enabled devices, forming a local relay network until connectivity is restored, thereby ensuring continuity of emergency communication.

The system further integrates secure user authentication, continuous GPS-based location tracking, responder acknowledgment mechanisms, and both offline and online AI components to ensure coordinated assistance, reliable alert delivery, and adaptive operation under varying network conditions.

Through this integrated approach, ResQNow provides a practical solution that reduces emergency response latency, enables guided intervention by untrained bystanders, and ensures resilient communication. The project outcomes benefit victims by improving access to timely assistance, bystanders by providing confidence and guidance during emergencies, emergency responders through improved situational awareness, and healthcare systems by supporting faster, more coordinated pre-hospital response.

1.6 Organisation of the Report

Chapter 1: Introduction illustrates the general overview of the proposed ResQNow: AI–AR First Aid & Emergency App, detailing the project's motivation, objectives, and the specific problem statement addressed.

Chapter 2: Literature Survey surveys existing emergency response systems, AI-based triage, AR in healthcare, and offline communication mechanisms, while highlighting limitations and research gaps in current solutions.

Chapter 3: Software Requirements Specification outlines the overall system requirements, including functional and non-functional needs, hardware and software specifications, development tools, and project constraints.

Chapter 4: Design and Methodology explains the system architecture, emergency detection workflow, AI classification, AR-guided assistance, GPS tracking, and BLE-based offline communication, along with experimental evaluation procedures.

Chapter 5: Implementation details the development of the mobile application, backend services, AI integration, AR guidance, SOS handling mechanisms, and offline communication logic.

Chapter 6: Testing and Validation presents testing strategies and results used to verify system reliability, covering functional, integration, performance, and offline communication validation.

Chapter 7: Application Results and User Interface demonstrates system results via application screens, highlighting SOS activation, AI-assisted handling, AR interfaces, and offline alert tracking.

Chapter 8: Conclusion and Future Work summarizes project contributions and outcomes, outlining future enhancements such as wearable integration, multilingual AR guidance, and on-device AI optimization.

Chapter 2

LITERATURE REVIEW

This chapter presents a comprehensive review of existing research in emergency response systems, augmented reality-based medical guidance, artificial intelligence-driven emergency detection and triage, and offline communication mechanisms. The review critically examines prior work to identify key limitations and research gaps that justify the development of the proposed ResQNow: AI-AR First Aid & Emergency App system.

2.1 Review of Related Works

Wang et al. [1] developed an augmented reality wound care guidance system using Microsoft HoloLens 2 to train nursing students on standardized wound-care procedures. The system overlays stepwise instructions and graphical hints directly on the patient's wound region to minimize procedural errors and improve adherence to clinical guidelines. Experimental evaluation in controlled laboratory settings demonstrated improved skill retention and reduced task completion time compared to conventional video-based instruction. However, the solution's dependence on expensive mixed-reality headsets, frequent sensor calibration requirements, and visual fatigue during prolonged use present significant barriers to widespread adoption. Furthermore, the system focuses exclusively on clinical training environments rather than real-time emergency first aid for untrained bystanders, and lacks integration with emergency alerting or triage workflows.

Kumar and Choudhary [2] proposed an AR-based burn management assistance system designed to improve care quality in rural and resource-limited healthcare settings. Their system presents visual overlays that guide healthcare workers through burn assessment, cooling, dressing, and referral recommendations. Pilot studies indicated better protocol adherence and increased confidence among semi-skilled health workers. Nevertheless, the solution remains heavily reliant on specialized AR devices with limited battery life and requires controlled indoor environments for stable tracking. The evaluation was conducted on a small sample

size, limiting statistical generalization to broader populations. Critically, the system lacks support for offline emergency alert propagation and integration with patient triage and transport coordination.

Rebol et al. [3] introduced a mixed-reality CPR coaching system that uses head-mounted displays to provide real-time visual feedback on chest compression depth, location, and frequency. The system leverages motion tracking sensors to overlay corrective hints and performance metrics within the user's field of view during practice sessions. User studies with medical students demonstrated improved compression rhythm and better adherence to resuscitation guidelines compared to conventional manikin training. However, the system requires specialized mixed-reality equipment, is restricted to simulation laboratories, and assumes a pre-planned training environment. It does not function as an on-demand assistance tool during real cardiac arrest events, nor does it support bystander-oriented CPR guidance in uncontrolled environments.

Abo-Zahhad et al. [4] designed an AI-powered AR glasses system for real-time emergency first-aid guidance using edge computing hardware. Their approach combines object detection, scene understanding, and AR overlays to guide laypersons during emergencies such as bleeding and trauma. The system runs on an NVIDIA Jetson-based platform, enabling on-device AI inference with minimal cloud reliance. Evaluation showed that users could follow step-by-step instructions more accurately than with traditional 2D instructions. However, reliance on dedicated AR glasses and embedded GPU platforms limits affordability and mass adoption. Additionally, the communication layer remains dependent on stable network connectivity for remote supervision.

Thomson et al. [5] presented a systematic review of AR and VR-based CPR training systems used for teaching resuscitation skills. The review showed that immersive technologies significantly improve learner engagement, knowledge retention, and self-efficacy compared to traditional instructor-led sessions. However, most systems were confined to skill laboratories or simulation centers, with high hardware and setup costs. The authors emphasized that existing AR/VR platforms are primarily training tools and not designed for deployment in real-life emergencies, where time, stress,

and connectivity constraints are critical. The absence of integration with real-time emergency alerts and severity assessment represents a significant limitation.

Mehta et al. [6] proposed a deep learning-based fall detection framework using smartphone accelerometer and gyroscope data to identify sudden falls among elderly users. The model employed convolutional and recurrent architectures to capture temporal motion patterns and achieved high accuracy under controlled experimental settings. However, performance degraded under real-world conditions due to sensor noise, inconsistent device placement, and user-specific motion variability. The system also focused solely on detecting falls without offering integrated emergency response, first-aid guidance, or triage capabilities.

Robinson and Alvarez [7] conducted a comprehensive review of smartphone-based fall detection applications available in research and app marketplaces. Their survey revealed that many apps rely on simple threshold-based algorithms or basic machine learning models, resulting in high false-positive rates during normal daily activities. They also observed significant battery consumption due to continuous sensor monitoring and background services. Additionally, most solutions lacked severity assessment, did not differentiate between minor and major falls, and offered limited functionality beyond sending basic SMS alerts. The authors concluded that future systems should incorporate intelligent triage, multimodal sensing, and context-aware alerting.

Jain et al. [8] explored AI-based smartphone pulse oximetry using camera-based photoplethysmography and regression models to estimate oxygen saturation. Their method employed signal processing and machine learning to extract SpO_2 values from fingertip videos captured by the phone camera. Under controlled lighting and stable positioning, the system produced clinically acceptable estimates compared to commercial pulse oximeters. However, in uncontrolled environments, performance was highly sensitive to ambient lighting, hand movement, and skin tone variations, resulting in increased error rates. This instability limits applicability in high-stress emergencies where conditions are unpredictable.

Chen et al. [9] proposed a smartphone-based vital sign monitoring system capable of estimating heart rate and respiratory rate using camera and inertial sensor data. Their

approach aimed to improve accessibility of basic physiological monitoring without dedicated medical devices. Although the system demonstrated good performance for healthy subjects under stable conditions, it required high computational resources and suffered from poor generalization when confronted with abnormal vital ranges or artifacts. The authors noted that the methodology was not optimized for time-critical emergency scenarios where resource constraints and rapid response are essential.

Rao and Banerjee [10] reviewed women safety and emergency alert applications that provide panic buttons, SOS messaging, and GPS location sharing. Their study found that most applications simply broadcast location and a short message to predefined contacts or police hotlines. Many solutions raised privacy concerns due to insecure data handling and continuous location tracking. Furthermore, existing apps lacked coordinated responder mechanisms, did not prioritize alerts by severity, and provided no medical guidance to victims in case of physical injury.

Evans and Li [11] introduced TCPRLink, a tele-CPR coordination system that enables dispatcher-assisted CPR through real-time communication between emergency call centers and bystanders. The system supports audio instructions and structured guidance to ensure correct CPR technique until professional responders arrive. Simulation studies reported improved chest compression quality and better adherence to dispatcher instructions. However, TCPRLink depends on trained dispatchers, requires stable internet or telephony connectivity, and does not use AR for visual assistance. It also does not function autonomously when professional personnel are unavailable.

Thomson et al. [12] performed a systematic analysis of AR and VR-based CPR training platforms across various educational and clinical environments. Their findings indicate that immersive environments significantly enhance user engagement, confidence, and skill retention compared to traditional classroom methods. Nevertheless, most studied systems were deployed as standalone training tools without linkage to real-time emergency response workflows. They lacked capabilities such as live patient monitoring, automated emergency classification, and direct alert routing to responders.

Ahmed et al. [13] presented DangerDet, an audio-based emergency detection system

that runs completely on-device to reduce dependency on cloud infrastructure. The system uses sound classification models to detect distress events such as screams, crashes, or alarms and then triggers alerts. Results showed that on-device inference is feasible and can reduce latency compared to server-side processing. However, DangerDet suffered from false positives in noisy environments and lacked contextual understanding of the incident, such as distinguishing between benign loud sounds and true emergencies. The system also did not provide first-aid guidance or multi-hop offline alert coordination.

Lin et al. [14] surveyed AR-assisted telemedicine platforms that enable remote experts to annotate and guide procedures performed by local caregivers. Their review covered applications in surgery, rehabilitation, and remote consultation, highlighting the potential of AR as a tool for expert-assisted interventions. However, they identified key limitations related to network reliability, as high-bandwidth, low-latency connections are often required, especially for streaming video and AR overlays. They also noted the lack of explicit support for time-critical emergency integration and limited long-term clinical validation.

Nair and Reddy [15] proposed MeshSOS, an IoT-based emergency alert system that uses mesh networking to propagate alerts across nodes in disaster-prone regions. Their design leverages low-power wireless modules to form a multi-hop communication fabric that can operate even when central infrastructure is damaged. Simulation results showed improved reliability and coverage compared to single-hop or infrastructure-dependent solutions. However, the system was validated mainly through simulations and small-scale prototypes, with limited real-world deployment. Furthermore, MeshSOS did not include AI-driven triage, context-aware prioritization, or AR-based first-aid assistance.

Green et al. [16] reviewed self-management mHealth systems designed for chronic disease monitoring, lifestyle management, and patient education. Their review found that many apps provided reminders, educational content, and logging features but lacked integrated intelligence for adaptive decision support. Offline capabilities were often minimal, limiting usability in connectivity-constrained contexts. Importantly, the authors highlighted a persistent absence of real-time first-aid assistance or support

for acute emergency episodes within self-management platforms.

Bajwa et al. [17] conducted a large-scale systematic review of AI-based emergency response systems, synthesizing over 400 studies on prediction, detection, and resource allocation in emergencies. The review highlighted that machine learning and deep learning models substantially improve hazard detection, dispatch optimization, and risk assessment across domains such as fire incidents, medical emergencies, and disaster management. However, most AI solutions were deployed as backend decision-support tools for professionals, with limited user-facing guidance and scarce integration into end-user mobile applications. The authors recommended future work that embeds AI into user-centric interfaces and combines it with robust communication mechanisms.

Raita et al. [18] compared traditional Emergency Severity Index (ESI) triage with machine learning-based triage models in emergency departments. Their study demonstrated that deep neural networks could predict critical care outcomes with higher accuracy than rule-based triage, achieving significantly better AUC values and reducing under-triage of high-risk patients. This evidence confirms the potential of AI to support decision-making in emergency settings. However, these models primarily operate on structured hospital data and require integration with electronic health records, making them unsuitable for direct use by laypersons.

Zhang et al. [19] proposed a real-time IoT-based emergency response and public safety alert system integrating sensors, edge nodes, and cloud services. The architecture achieved sub-second alerting latency and supported large-scale deployments with thousands of devices. Their system demonstrated automatic detection of critical incidents such as fires and accidents, followed by rapid dissemination of alerts to responders and citizens. Nevertheless, the solution relies heavily on dedicated IoT infrastructure and stationary sensors embedded in the environment. It does not provide personalized first-aid guidance to affected individuals or support peer-to-peer offline communication on mobile devices.

Yilmazer et al. [20] reviewed Bluetooth Low Energy (BLE) mesh networking applications and discussed their suitability for smart buildings, industrial automation, and disaster communication. They emphasized that BLE mesh

supports many-to-many communication, is energy-efficient, and can be deployed using commodity hardware. The authors highlighted that BLE mesh networks are resilient to single-point failures and can provide coverage in indoor environments where other technologies may struggle. These properties make BLE mesh attractive for emergency communication scenarios.

Raza et al. [21] introduced Bluemergency, a Bluetooth mesh-based emergency communication system intended for post-disaster scenarios. The system enables smartphones and IoT devices to exchange short emergency messages using multi-hop Bluetooth connections without relying on centralized infrastructure. Prototype implementations demonstrated feasible message propagation in smart office and smart home environments. However, the system primarily focused on connectivity and did not address emergency content classification, user guidance, or integration with first-aid workflows.

Li et al. [22] examined global emergency systems based on integrating Wireless Personal Area Networks (WPAN) such as BLE with Low-Power Wide-Area Networks (LPWAN) like LoRa. Their architecture aimed to provide local device-to-device communication along with long-range fallback connectivity in large-scale emergencies. They demonstrated that combining BLE and LoRa can improve coverage, reduce energy consumption, and support multi-hop alert propagation over diverse terrains. While their focus was on infrastructural design and network performance, the work underscores the importance of multi-layer connectivity in resilient emergency systems.

Sharma et al. [23] presented RescueNow, a real-time SOS and predictive women's safety system that integrates a smartphone app with GPS tracking and cloud-based services. The system supports multiple discreet triggers such as button press, shake gesture, and voice activation, and on activation it sends the user's live location and identity to selected contacts and, where configured, law-enforcement numbers. It also performs silent audio or video recording to preserve incident evidence, and uses machine learning on historical incident and location data to predict crime-prone regions and warn users entering those zones. Experimental evaluation showed reliable alert delivery and improved perceived safety among participants, but the

work focuses mainly on personal safety scenarios and does not provide medical triage, first-aid guidance, or offline mesh-based alert propagation.

Hariharan et al. [24] proposed an SOS alert band system for women that uses a wearable wristband with a panic button, GPS, and wireless connectivity to send distress alerts. When activated manually or through detected abnormal motion, the band transmits the user's coordinates and basic status information to guardians, police contacts, or monitoring centers via Bluetooth-linked phones, Wi-Fi, or cellular networks. Field deployments in rural and tribal regions reported average response times on the order of 10–15 minutes and positive user feedback regarding usability and reliability. However, the system depends on dedicated hardware, requires pairing and charging, and is oriented toward security incidents rather than broader medical emergencies or first-aid support.

O'Sullivan et al. [25] investigated a low-cost telemedicine architecture for emergency medical services that connects ambulances, control centers, and hospitals using audio–video links and shared electronic records. Their approach enables remote physicians to support paramedics in making transport decisions, initiating treatment, and avoiding unnecessary emergency department visits. Pilot implementations showed that many cases could be safely managed with teleconsultation, improving resource utilization and clinical decision-making. At the same time, the model assumes trained staff, institutional workflows, and reasonably stable network connectivity, making it less suitable as a standalone solution for bystanders at the scene of an incident.

Murugan et al. [26] developed an AI-driven virtual health assistance chatbot that uses natural language processing to interpret user-described symptoms and provide preliminary guidance. The system extracts key symptom phrases from free text, queries machine-learning models and medical sources, and responds with basic advice on likely conditions and urgency. Usability studies indicated good user satisfaction and short response times for common query patterns, though performance declined for ambiguous or poorly described complaints. The work shows how conversational interfaces can support symptom assessment on mobile devices, but it does not target real-time emergencies or integrate with structured SOS and alerting workflows.

Das et al. [27] proposed an AI-based medical chatbot that combines machine-learning classifiers with rule-based logic to predict possible diseases from user input. The architecture uses text preprocessing and feature extraction to map symptom descriptions into model inputs, and then ranks likely diagnoses and suggested actions such as self-care or medical consultation. Evaluation on a symptom–disease dataset demonstrated high accuracy, precision, and recall for a range of common conditions, supporting the feasibility of automated symptom triage. However, the system is oriented toward general outpatient decision support rather than time-critical emergencies, and it does not couple its predictions with location-aware SOS dispatch or augmented-reality guidance.

2.2 Research Gap Analysis

The literature review indicates that existing emergency response solutions address isolated components rather than delivering an integrated end-to-end system.

Most AR-based medical guidance systems are designed for clinical training and depend on costly head-mounted devices, limiting their accessibility and usability for the general public during real emergencies. These systems are unsuitable for untrained bystanders operating in uncontrolled environments.

AI-driven emergency detection models are largely confined to hospital backends or research settings and rely on structured clinical data. Consumer-level implementations suffer from false alarms, limited contextual awareness, and lack integrated first-aid guidance or severity-based triage.

Current emergency alert applications primarily provide basic SOS and GPS sharing features. They lack intelligent severity assessment, coordinated responder prioritization, and secure data handling, reducing their effectiveness during critical situations.

Offline communication solutions such as BLE mesh networks focus only on message relay and do not integrate AI-driven triage, user guidance, or complete emergency workflows. Similarly, telemedicine systems depend on stable connectivity and professional infrastructure, making them unsuitable for autonomous first-response

scenarios.

Furthermore, very few systems employ hybrid architectures that combine cloud intelligence with offline fallback mechanisms, limiting reliability during network disruptions.

Overall, there is a clear absence of a unified, intelligent, and connectivity-resilient emergency response platform that combines AI-based emergency classification, AR-guided first aid on smartphones, and reliable offline alert propagation for untrained bystanders.

2.3 Scope Definition

The scope of **ResQNow: AI-AR First Aid & Emergency App** ensures feasibility within an academic project.

Timeframe: Single academic project cycle.

Geographical Context: Urban/semi-urban areas with variable connectivity.

Operational Environment: Smartphone-based emergencies (cardiac arrest, bleeding, trauma) for untrained bystanders.

Functional Boundaries: AI classification, AR first-aid, SOS alerts, GPS sharing, BLE offline communication.

Target Users: Victims, bystanders, nearby responders.

Technical Constraints: Standard Android smartphones only.

Limitations: No clinical diagnosis or disaster coordination.

ResQNow bridges research gaps with intelligent emergency response on commodity devices.

Chapter 3

SYSTEM REQUIREMENTS

This chapter presents the system requirements of the ResQNow emergency response system, outlining hardware and software specifications, functional and non-functional requirements, and development tools necessary to support AI-based emergency classification, AR-guided first-aid assistance, reliable SOS communication, and scalable real-time alert delivery.

3.1 Hardware Requirements

The hardware requirements are defined to ensure smooth development, testing, and deployment of the ResQNow system under realistic operating conditions. Adequate computational resources are essential to support simultaneous execution of mobile emulators, backend services, AI model inference, and AR rendering workflows. The specified hardware configurations aim to balance performance, reliability, and cost-effectiveness while ensuring system stability during emergency response simulations and real-time testing. In addition, field testing may involve continuous GPS access, video processing, and BLE communication, which demand reliable device performance under prolonged usage. Therefore, selection of appropriate development hardware significantly improves productivity, reduces latency during debugging, and ensures realistic behaviour under crisis-like operational environments.

3.1.1 Development Workstation Requirements

The development of ResQNow requires workstations capable of running modern mobile development tools, emulators, and backend services simultaneously. A capable workstation ensures faster build times, smoother emulator execution, and efficient handling of AR models during development. Systems with multi-core CPUs and GPU acceleration are preferred to handle real-time rendering and machine learning workloads efficiently. Stable internet connectivity is also required for

cloud-based deployment, Firebase integration, and remote logging during backend testing.

Recommended Mobile Device Requirements

To conduct effective real-world testing, mobile devices must meet certain baseline specifications to support AR visualization, BLE messaging, GPS positioning, and cloud synchronization reliably. Devices with higher RAM and processing power reduce frame drops during AR guidance, while larger storage allows saving logs, media evidence, and emergency reports locally. The following minimum configuration is recommended:

- **OS:** Android 11.0+ or iOS 15.0+
- **Processor:** Octa-core ARM processor
- **RAM:** Minimum 4 GB
- **Storage:** 64 GB
- **Display:** Full HD+ smartphone display
- **Camera:** Rear camera with AR support
- **Connectivity:** 4G/5G, Wi-Fi, Bluetooth 5.0+
- **Battery:** 4000 mAh or higher
- **AR Support:** ARCore (Android) / ARKit (iOS)

Critical Hardware Features

The identified hardware capabilities directly affect the accuracy, responsiveness, and overall usability of ResQNow during emergencies. Sensors and connectivity modules play a key role in real-time data collection and delivery. Devices lacking AR support can still execute the app but will fall back to non-AR instructional mode with reduced visual interactivity. The following components are crucial for seamless first-aid assistance and offline communication:

- **Bluetooth Low Energy (BLE):** Required for offline SOS relay with peripheral and central mode support for reliable multi-hop mesh networking in emergencies.
- **GPS with A-GPS:** Necessary for accurate real-time location tracking with Assisted GPS for faster position acquisition during emergency situations.
- **Motion Sensors:** Accelerometer and gyroscope mandatory for AR-based first-aid guidance and precise device orientation tracking.
- **Camera with Autofocus:** Required for AR overlay rendering, injury visualization, and accurate real-world alignment of virtual instructions.
- **ARCore/ARKit Compatibility:** Devices must be certified compatible for optimal AR functionality. Non-compatible devices fall back to video-based guided assistance.

3.2 Software Requirements

The ResQNow system follows a modular, service-oriented architecture integrating AI, AR, cloud services, and wireless communication for real-time emergency assistance. The architecture emphasizes low latency, fault tolerance, security, and scalability, ensuring reliable operation. The system is organized into four layers, each serving specific functions while maintaining loose coupling through well-defined interfaces.

3.2.1 Software Architecture Overview

The ResQNow system follows a modular, service-oriented architecture integrating AI, AR, cloud services, and wireless communication for real-time emergency assistance. The architecture emphasizes low latency, fault tolerance, security, and scalability, ensuring reliable operation in critical situations. It supports distributed deployment and seamless module interaction, enabling efficient updates and feature expansion. The system is organized into four distinct layers, each serving specific functions while maintaining loose coupling through well-defined interfaces for improved maintainability and long-term adaptability.

3.2.2 Mobile Application Layer

The Mobile Application Layer serves as the primary user interface of the ResQNow system and is implemented using the Flutter framework for cross-platform support on Android and iOS devices. This layer manages user interaction, sensor access, and emergency triggering functions.

Key components and responsibilities include:

- **User Authentication Module:** Provides secure login and registration using Firebase Authentication with session management.
- **SOS Activation Interface:** Enables emergency triggering through an on-screen button or voice command for quick access.
- **GPS Location Service:** Captures real-time user location data during emergency situations.
- **AR First-Aid Module:** Displays AR-based visual guidance for first-aid procedures using ARCore or ARKit.
- **BLE Communication Handler:** Supports offline SOS relay using Bluetooth Low Energy.

3.2.3 Backend Services Layer

The Backend Services Layer is developed using Python with the FastAPI framework and handles all server-side operations, data management, and emergency coordination logic.

Core backend components include:

- **API Gateway:** Exposes RESTful endpoints for SOS handling and user management.
- **Incident Management Service:** Tracks emergency status, timestamps, and responder actions.

- **Data Persistence Layer:** Stores user and emergency data using Firebase Firestore.
- **Alert Orchestration Engine:** Manages multi-channel emergency notification delivery.

3.2.4 AI Intelligence Layer

The AI Intelligence Layer enables automated understanding and prioritization of emergency situations to assist in rapid response.

This layer includes:

- **Conversational AI Engine:** Interprets user-described emergencies using cloud-based language models.
- **Emergency Classification System:** Identifies emergency type and priority level.
- **Severity Assessment Module:** Determines urgency based on symptoms and context.
- **Rule-Based Classifier:** Provides offline fallback classification when AI services are unavailable.

3.2.5 Communication and Notification Layer

The Communication Layer ensures reliable delivery of emergency alerts using multiple communication channels.

Components include:

- **Push Notifications:** Real-time alerts via Firebase Cloud Messaging.
- **SMS Alerts:** Emergency messages sent to contacts using SMS gateways.
- **Email Notifications:** Detailed emergency updates through email services.
- **BLE Mesh Network:** Offline SOS forwarding between nearby devices.

3.2.6 Development Tools and Technologies

The ResQNow system utilizes modern development tools and cloud platforms to support efficient development and deployment.

Programming Languages and Frameworks

- **Dart:** Language used for Flutter mobile application development
- **Python:** Backend and AI service development
- **Flutter SDK:** Cross-platform framework for Android and iOS
- **FastAPI:** Python framework for RESTful API development

Cloud Services and Infrastructure

- **Firebase Firestore:** Real-time NoSQL database for application data
- **Firebase Authentication:** Secure user authentication service
- **Firebase Cloud Messaging:** Push notification delivery
- **Google Cloud Platform:** Backend hosting and deployment

AI and Augmented Reality Services

- **OpenAI / Gemini API:** Emergency understanding and classification
- **ARCore / ARKit:** Augmented reality support for first-aid guidance

Communication and Development Tools

- **Twilio API:** SMS-based emergency alerts
- **SendGrid API:** Email notification service
- **Android Studio / Xcode:** Mobile application development
- **Git / GitHub:** Version control and collaboration

Chapter 4

DESIGN AND METHODOLOGY

This chapter presents the technical design and experimental methodology used for developing and evaluating the proposed emergency response system. It outlines the research objectives, measurement parameters, system architecture, UML diagrams, experimental procedures, error considerations with mitigation strategies, and the data analysis techniques applied for real-world performance evaluation.

4.1 Objective of the Study

The primary objective of this study is to design, implement, and evaluate an intelligent emergency response system that enhances response time and user guidance during emergencies. The work aims to develop a reliable mobile solution integrating real-time decision support, communication features, and AR-based first-aid assistance. The research objectives include:

- To develop a rapid SOS trigger mechanism capable of initiating alerts within 3 seconds using optimized UI interactions and event handling.
- To implement a hybrid AI-based emergency classification model combining cloud inference with rule-based fallback to achieve over 85% detection accuracy.
- To design an AR-based first-aid assistance module with under 2-second startup time providing step-wise CPR, AED, and bleeding control guidance.
- To develop a BLE-based offline communication system targeting over 80% successful delivery across a cumulative 100-meter mesh relay range.
- To analyze and reduce end-to-end response latency including GPS acquisition, network delays, server processing, and multi-channel notification dispatch.
- To evaluate system resource consumption covering battery usage, CPU load, memory usage, and network bandwidth across multiple device variants.

- To validate usability and reliability through controlled field tests simulating real-world emergencies with diverse environmental conditions.

4.2 Measurement Parameters

The system performance is evaluated using the following quantitative parameters:

4.2.1 Latency Metrics

- **SOS Dispatch Time ($T_{dispatch}$):** Time elapsed from SOS button press to alert reception by emergency contacts, measured in milliseconds. Target: $T_{dispatch} <$ 3000 ms under normal network conditions.
- **AR Initialization Latency (T_{AR}):** Time required from AR module invocation to display of first visual overlay, measured in milliseconds. Target: $T_{AR} < 2000$ ms.
- **GPS Acquisition Time (T_{GPS}):** Time from location request to first valid coordinate fix, measured in milliseconds.
- **Network Transmission Time ($T_{network}$):** Time for data packet transmission from client to server acknowledgment, measured in milliseconds.

4.2.2 Accuracy Metrics

- **AI Classification Accuracy (A_{class}):** Percentage of correct emergency type identifications, calculated as:

$$A_{class} = \frac{\text{Correct Classifications}}{\text{Total Test Cases}} \times 100\% \tag{4.1}$$

  Target: $A_{class} > 85\%$

- **Severity Assessment Accuracy ($A_{severity}$):** Percentage of correct severity level assignments (high/moderate/low). Target: $A_{severity} > 80\%$

- **GPS Location Accuracy (ϵ_{GPS}):** Horizontal position error in meters compared to ground truth coordinates. Target: $\epsilon_{GPS} < 10$ meters under open sky.

4.2.3 Reliability Metrics

- **BLE Relay Success Rate (R_{BLE}):** Percentage of messages successfully delivered through offline relay, calculated as:

$$R_{BLE} = \frac{SuccessfullyDeliveredMessages}{TotalBroadcastMessages} \times 100\% \tag{4.2}$$

  Target: $R_{BLE} > 80\%$ within 100 m range.

- **Notification Delivery Rate (R_{notify}):** Percentage of alerts successfully received by emergency contacts across all channels.

4.2.4 Resource Utilization Metrics

- **Battery Consumption ($P_{battery}$):** Power draw during active operation, measured in milliampere-hours (mAh) per hour.

- **Network Bandwidth ($B_{network}$):** Total data transmitted per SOS event, measured in kilobytes (KB).

- **CPU Utilization (U_{CPU}):** Average processor usage during AR rendering and AI processing, measured as percentage.

- **Memory Footprint (M_{app}):** Application memory consumption, measured in megabytes (MB).

4.3 Measurement Method

4.3.1 Prototype Development

A functional prototype of the ResQNow system was developed using production-grade technologies and deployed on multiple physical Android devices including Google Pixel 6, OnePlus 9, and Samsung Galaxy S21, representing diverse hardware configurations, screen sizes, and Android versions (Android 11, 12, and 13). The prototype implements all core system functionalities including SOS triggering, GPS tracking, AI classification, AR guidance, BLE relay, and multi-channel notifications.

4.3.2 Latency Measurement Methodology

System timestamps are recorded at critical execution points using high-precision system clocks with microsecond resolution:

- t_0: SOS button press event timestamp (client-side)
- t_1: GPS location acquisition completion timestamp
- t_2: Network transmission initiation timestamp
- t_3: Backend server reception timestamp (server-side)
- t_4: Database write completion timestamp
- t_5: Notification dispatch timestamp
- t_6: Alert reception timestamp on emergency contact device

End-to-end latency is calculated as: $T_{dispatch} = t_6 - t_0$

Component-level latencies are derived as:

- GPS acquisition time: $T_{GPS} = t_1 - t_0$
- Network transmission time: $T_{network} = t_3 - t_2$

- Backend processing time: $T_{backend} = t_5 - t_3$
- Notification delivery time: $T_{notification} = t_6 - t_5$

Timestamps are synchronized between client and server using Network Time Protocol (NTP) to ensure accurate distributed timing measurements with sub-second precision.

4.3.3 AI Classification Validation

A test dataset of 100 emergency scenarios was prepared with ground truth labels established through consultation with emergency medical protocols and expert review. Each scenario includes a textual description simulating user input and correct classifications for emergency type and severity level. The AI classification module processes each test case, and outputs are compared against ground truth labels. Classification accuracy is calculated using the confusion matrix method, with additional metrics including precision, recall, and F1-score computed for each emergency category.

4.3.4 AR Performance Profiling

AR initialization latency and rendering performance are measured using Android Profiler integrated within Android Studio. The profiler captures:

- ARCore SDK initialization time from API call to ready state
- Surface detection time for environment mapping
- 3D model loading and rendering time
- Frame rate (FPS) during active AR guidance session
- GPU utilization and texture memory allocation

Measurements are repeated across 20 trials under consistent lighting conditions and camera angles to establish statistical reliability.

4.3.5 BLE Relay Testing Procedure

Controlled outdoor experiments are conducted in an open field environment to minimize signal interference and multipath effects. The experimental setup includes:

- One originating device broadcasting encrypted SOS messages
- 2 to 5 relay devices positioned at measured distances (10m, 30m, 50m, 100m)
- One gateway device with internet connectivity for message upload
- Measurement tape for precise distance marking
- Stopwatch for timing message propagation

For each configuration (varying distances and node counts), 50 test messages are broadcast. Success is recorded when the gateway device receives and uploads the message to the backend within 60 seconds. The BLE relay success rate is calculated as the percentage of successful deliveries. Signal strength (RSSI) is logged at each hop to analyze propagation characteristics.

4.3.6 Network Condition Simulation

Android Developer Options traffic shaping is used to simulate poor network conditions representative of real-world emergency scenarios:

- **Normal conditions:** 4G LTE with 50ms latency, no packet loss
- **Degraded conditions:** 3G speeds with 200ms latency, 5% packet loss
- **Poor conditions:** 2G speeds with 500ms latency, 15% packet loss
- **Offline conditions:** No cellular or Wi-Fi connectivity

System performance metrics are measured under each condition across 30 trials to establish statistical distributions and identify performance degradation patterns.

4.3.7 Resource Utilization Measurement

Device profiling tools capture resource consumption during typical usage scenarios:

- **Battery consumption:** Measured using Android Battery Historian, capturing power draw during 1-hour active emergency operation including GPS tracking, AR rendering, and BLE broadcasting
- **Network bandwidth:** Measured using Charles Proxy to intercept and analyze HTTP/HTTPS traffic, recording payload sizes for SOS requests, classification API calls, and notification delivery
- **CPU and memory:** Measured using Android Profiler during AR rendering, AI processing, and background BLE scanning, capturing peak and average utilization

4.4 System Design Specifications

This section presents the detailed system design through architecture diagrams and Unified Modeling Language (UML) diagrams that specify the structural and behavioral aspects of the ResQNow emergency response system.

4.4.1 System Architecture

The ResQNow system adopts a three-tier client-server architecture ensuring separation of concerns, scalability, and fault tolerance. The architecture is organized into distinct layers that communicate through well-defined interfaces and protocols.

Figure **??** illustrates the complete system architecture showing the three primary architectural layers and their constituent components. The **Mobile Application Layer** (shown on the left) executes on user devices and comprises the Flutter Mobile App as the main user interface, SOS Trigger module handling both manual button press and voice command activation, GPS Location Capture module interfacing with device positioning hardware, AR-based First Aid Guidance module

providing visual procedural instructions, and Bluetooth Low Energy (BLE) Offline Relay module enabling mesh networking for internet-unavailable scenarios.

The **Backend Services Layer** (shown in the center) operates as the central coordination hub deployed on Google Cloud Platform. It includes the FastAPI Backend Server handling HTTP API requests and orchestrating system operations, Authentication via Firebase Auth module securing user sessions through JWT tokens, AI Emergency Classification Module analyzing user descriptions to determine emergency type, Severity Assessment Engine determining urgency levels (high/moderate/low), and Firebase Firestore database providing persistent storage for user profiles and incident records.

The **Notification Layer** (shown on the right) ensures multi-channel alert delivery through Firebase Cloud Messaging for instant push notifications to app users, Twilio service for SMS delivery to contacts without app installation, and SendGrid service for email alerts providing detailed information with location maps. Data flows from the mobile application through the backend services to the notification channels, with arrows indicating synchronous request-response patterns (solid lines) and asynchronous event-driven communication (implicit in the architecture). This layered design enables independent scaling of components, fault isolation preventing cascading failures, and graceful degradation when individual services become unavailable.

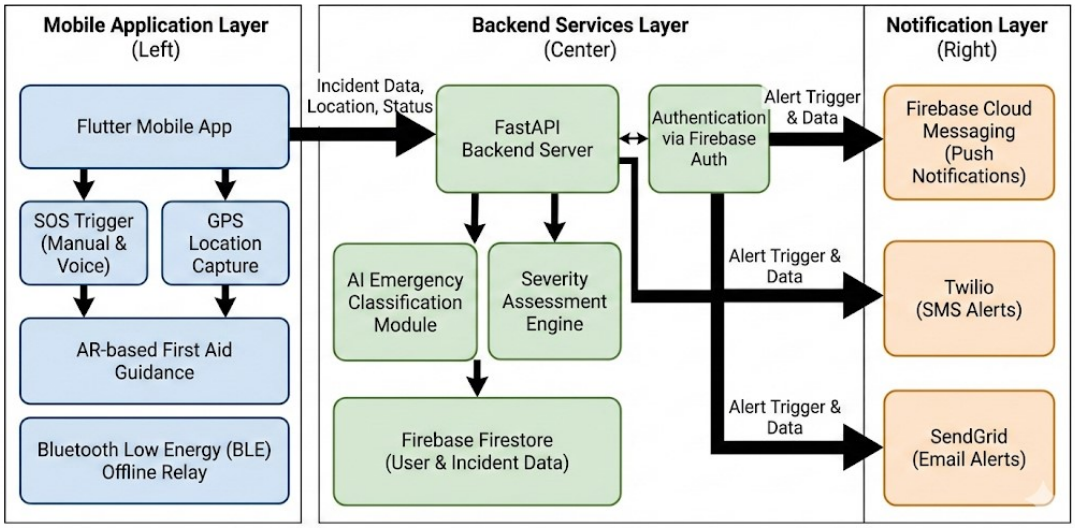

Figure 4.1: Overall System Architecture of the ResQNow Emergency Response System

4.4.2 Use Case Diagram

The use case diagram provides a high-level functional specification of the ResQNow system by identifying system actors and their interactions with system capabilities. This diagram establishes the system boundary, defines functional requirements, and serves as the basis for test case development and requirement traceability.

Figure **??** presents the complete use case diagram showing three primary actors and their associated use cases. The **User** (primary actor, shown on the left) represents individuals who may face emergencies and interact with the system through multiple use cases: Register/Login for account creation and authentication, Manage Emergency Contacts to designate notification recipients, Trigger SOS to activate emergency alerts, Provide AR First-Aid Guidance to receive real-time procedural instructions, and Track Emergency Status to monitor responder acknowledgments and estimated arrival times.

Within the system boundary (large rectangle labeled "ResQNow Emergency Response System"), internal use cases represent core system functionalities. The Capture Location use case (shaded) has include relationships (shown as dashed arrows with include stereotype) with Trigger SOS, indicating that location capture

is always executed as part of SOS activation. The Classify Emergency use case determines emergency type based on user input. The Assess Severity use case evaluates urgency levels to guide system behavior. The Send SOS Alert use case handles notification dispatch, which has an extend relationship (shown as dashed arrow with extend stereotype) with Offline SOS Relay, indicating that BLE relay is conditionally activated only when internet connectivity is unavailable.

The Notify Emergency Contacts use case (shaded on the right) connects to both the **Emergency Contact** actor (shown on the upper right) who receives and views alert notifications, and the **Medical Responder** actor (shown on the lower right) representing nearby users who can acknowledge and respond to emergencies. The Notify Medical Responders use case and Receive Acknowledgment use case facilitate responder coordination. The **ResQNow Backend System** actor (shown on the bottom right) represents external system components handling alert processing and coordination logic.

Include relationships indicate mandatory dependencies where the including use case cannot complete without executing the included use case. Extend relationships indicate optional behaviors that may occur under specific conditions. This use case specification defines 12 distinct functional capabilities, 4 actors, and multiple relationship types that guide subsequent detailed design and implementation phases.

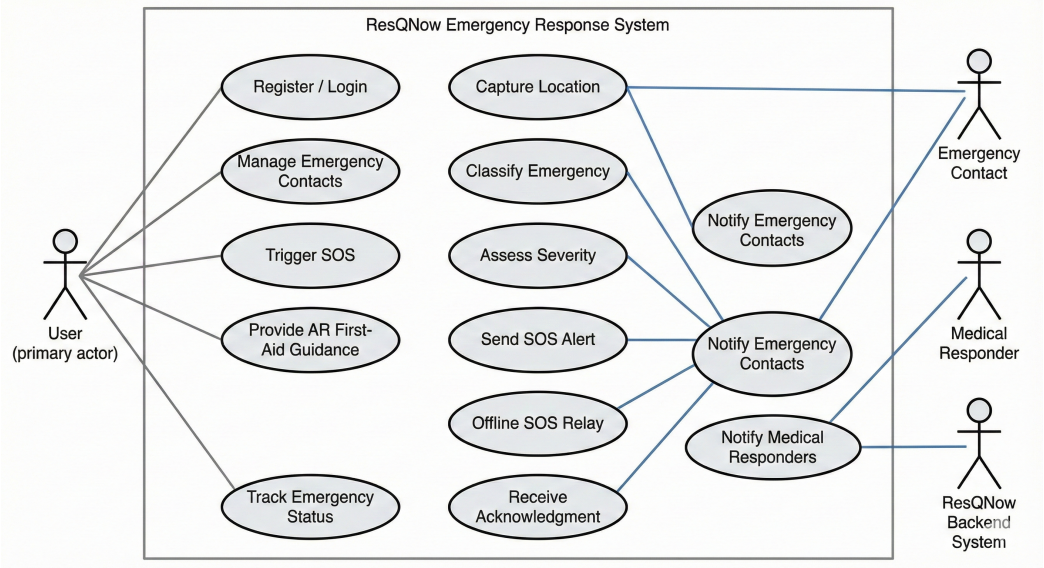

Figure 4.2: Use Case Diagram of the ResQNow System

4.4.3 Activity Diagram for SOS Emergency Response Workflow

The SOS activation workflow represents the most critical operational sequence in the ResQNow system, executing under time-critical conditions with minimal user burden. This workflow must maximize response speed while ensuring data accuracy and multi-channel notification delivery.

Figure **??** depicts the complete SOS emergency response activity flow using standard UML activity diagram notation. The workflow begins at the Start node (filled circle at top) and proceeds through the following sequence:

Decision Point 1 - SOS Trigger Method: The first decision diamond determines how the SOS was initiated. If the user selects Manual SOS (left branch), they proceed to Select Severity where they explicitly choose the emergency level (critical, moderate, minor) through UI controls. If the user initiates AI Chat (right branch), they enter the Analyze Conversation state where the system processes their natural language description to automatically determine emergency characteristics. The AI path includes a loop back to Continue Chat if no emergency is detected, allowing extended conversation. When an emergency is confirmed ([Yes] branch), the flow proceeds to Raise SOS.

Convergence and Sequential Processing: Both the manual and AI-assisted paths converge at the Raise SOS action (rounded rectangle), demonstrating that regardless of initiation method, the subsequent workflow is identical. The system then executes Capture GPS Location to acquire current coordinates using device positioning services.

Alert Broadcasting: Following location capture, the Broadcast SOS to all users action disseminates the emergency alert to the backend server (if online) or nearby devices (if offline, using BLE relay described in the next activity diagram). The alert includes user identification, GPS coordinates, severity level, and timestamp.

Responder Coordination: The Users view alert and proximity action represents nearby responders evaluating the emergency on their devices. The second decision diamond (Decision: Any user responds?) determines if anyone acknowledges the alert.

If No, the flow proceeds to SOS remains open, maintaining the alert in active state. If Yes, the system executes three parallel actions: Lock responder, Disable response button for others, and Show live location via Google Maps.

Termination: The parallel activities reconverge at the join node, and the workflow terminates at the End node.

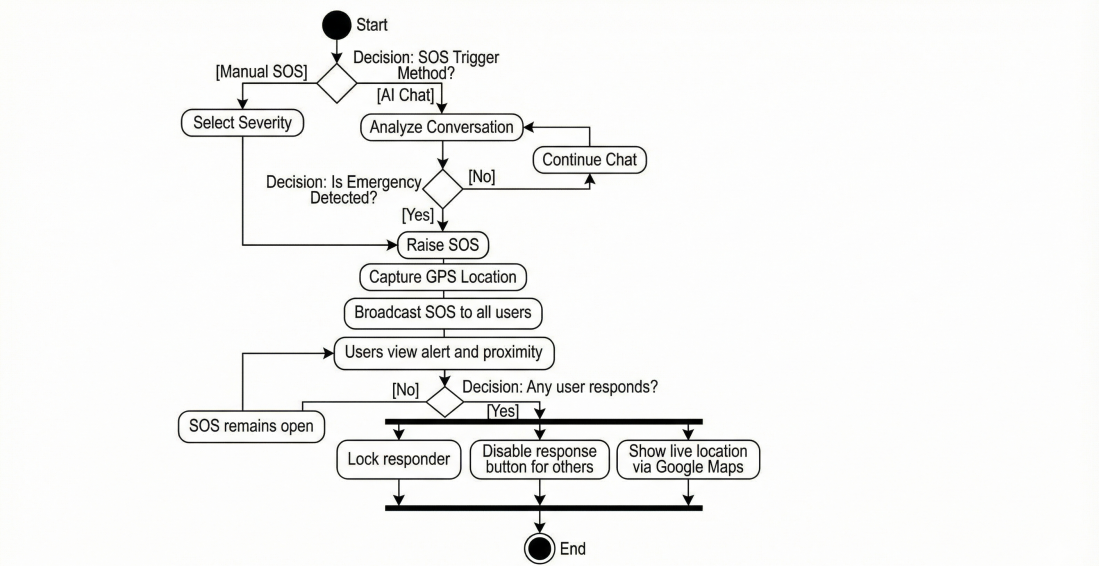

Figure 4.3: Activity Flow Diagram of Emergency SOS Processing

4.4.4 Activity Diagram for BLE Offline Relay Workflow

The BLE offline relay mechanism addresses a critical vulnerability in emergency alert systems that depend entirely on cellular or internet connectivity. This workflow enables emergency message propagation through dynamic ad-hoc mesh networks using Bluetooth connectivity between nearby devices.

Figure **??** illustrates the BLE offline relay activity flow showing how encrypted emergency messages propagate through multi-hop device forwarding.

Trigger and Connectivity Check: The SOS triggered action initiates the workflow. If internet connectivity is available, the workflow terminates immediately. If unavailable, the offline relay mechanism activates.

Encryption and Broadcasting: The Encrypt SOS packet action applies AES-128 symmetric encryption. The Broadcast via BLE action transmits the encrypted

message using BLE advertisements.

Discovery and Relay Loop: Nearby devices scan continuously. If no device is found, broadcasting continues with backoff. If a device is found, the message is forwarded.

Relay Device Processing: Devices increment hop count and re-broadcast until an internet-enabled gateway device is reached.

Confirmation and Termination: After backend upload, acknowledgment messages propagate back to the originator.

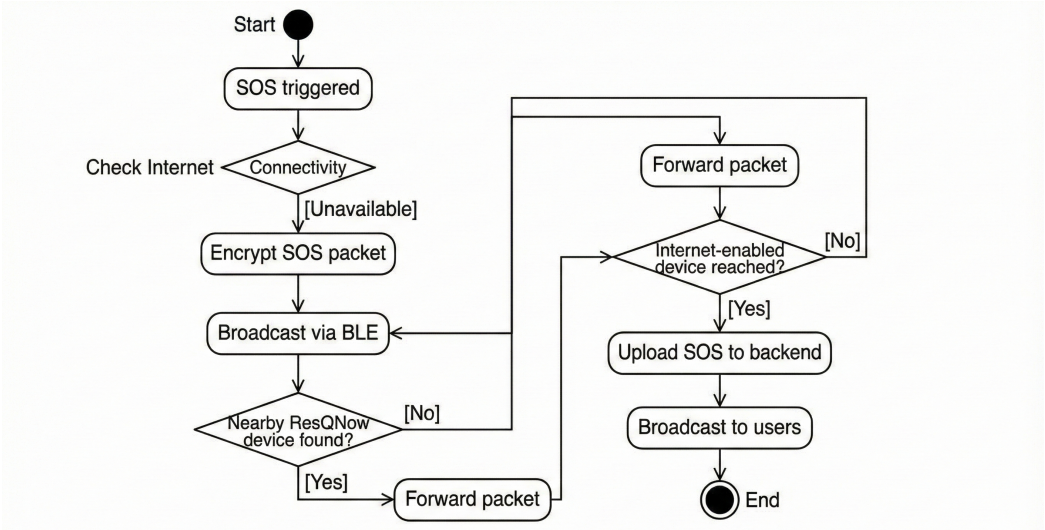

Figure 4.4: Offline SOS Relay Mechanism Using Bluetooth Low Energy

4.4.5 Activity Diagram for AI-Based Emergency Classification Workflow

The emergency classification workflow implements a hybrid artificial intelligence approach combining cloud-based conversational intelligence with rule-based severity mapping to ensure reliable classification across varying network conditions.

Figure **??** presents the rule-based offline emergency classification flowchart showing the fallback mechanism when cloud AI services are unavailable.

Connectivity Decision: Determines whether cloud AI or offline rules are used.

Keyword Extraction: Performs preprocessing and symptom keyword identification.

Rule-Based Symptom Matching: Matches extracted keywords against severity rules.

Confidence Scoring: Computes confidence based on severity weights and keyword frequency.

Classification Decision: Determines severity category (High, Moderate, Low).

Severity Assignment and Action Selection: Triggers Immediate SOS, User Confirmation, or Guidance Only.

Workflow Termination: All paths converge to the End state.

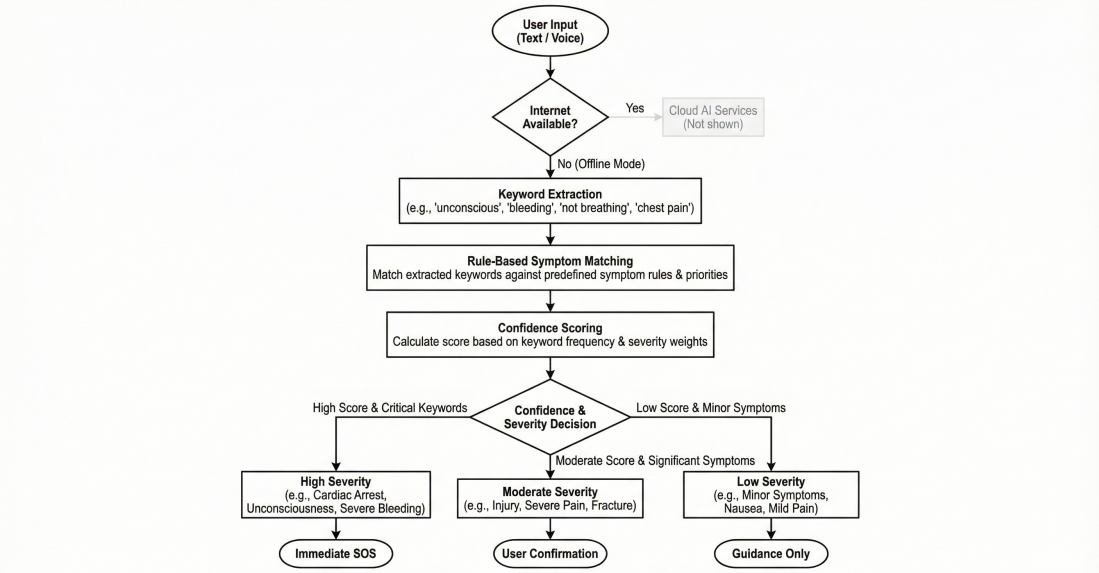

Figure 4.5: Rule-Based Offline Emergency Classification Flowchart

4.4.6 Sequence Diagram for Complete SOS Lifecycle

Sequence diagrams model the time-ordered interaction between system components, showing precise message exchanges and method invocations during specific scenarios. Unlike activity diagrams that focus on control flow logic, sequence diagrams emphasize inter-object communication and chronological ordering of events.

Figure **??** presents the complete SOS lifecycle sequence diagram showing interactions between six system participants arranged horizontally: User (leftmost actor), Mobile App, AI Chatbot, Backend Server, Other App Users (Responders), and Google Maps (rightmost actor). Vertical dashed lines (lifelines) represent each

participant's existence over time, with time progressing downward. Thin rectangular boxes on lifelines (activation boxes) indicate periods of active processing.

SOS Initiation Phase: The sequence begins with two alternative flows (alt frame labeled "SOS Initiation" at top left). In the [Manual Initiation] scenario (top branch), the User performs action 1: Initiate SOS (Manual) sending a message to Mobile App, which executes action 2: Select Severity (e.g., Critical) allowing manual severity selection through UI dropdown. In the [AI Chat Initiation] scenario (bottom branch), the User performs action 1a: Start Chat & Provide Symptoms sending conversational text to Mobile App, which forwards the message to AI Chatbot for action 2a: Analyze Conversation & Symptoms (shown as synchronous call with solid arrow). If the AI detects an emergency, it performs action 3a: Trigger SOS Automatically (if required) sending a command back to Mobile App. Both branches converge after the alt frame.

Location Capture: Following SOS initiation, the Mobile App sends action 4: Request GPS Location to itself (reflexive arrow on Mobile App lifeline), which returns action 5: Return Current Coordinates (dashed arrow indicating response message). This captures the user's position for alert metadata.

Backend Transmission: The Mobile App sends action 6: Send SOS Request (Location, Severity, User ID) to Backend Server (long solid arrow crossing to server lifeline) using HTTPS POST request. The server processes the request and performs action 7: Broadcast SOS Alert (Location, Severity) to Other App Users (Responders), shown as a message to the responder lifeline. This notification appears on nearby users' devices.

Responder Evaluation and Response: Upon receiving the alert, Other App Users (Responders) execute action 8: Evaluate Alert (Proximity, Availability) (reflexive arrow) to assess whether they can provide assistance based on distance and current availability. If a responder decides to help, they send action 9: Click "I'll Respond" (Responder ID) back to Backend Server. The server executes action 10: Lock SOS & Assign Responder (dashed arrow indicating internal processing), implementing atomic database transaction to prevent race conditions where multiple responders simultaneously claim the same emergency.

Status Update and Navigation: After assigning the responder, the Backend

Server sends action 11: Disable Response Button & Show Responder Assigned to Other App Users (Responders), updating UI state for all other potential responders to prevent duplicate acknowledgments. The server also sends action 12: Notify User of Responder Assignment back to Mobile App, informing the victim that help is on the way. The Mobile App then sends action 13: Open Maps with Live Victim Location to itself, which forwards action 14: Open Maps with Live Victim Location (for Responder) to Google Maps (rightmost participant), launching navigation interface showing real-time victim position for responder guidance.

Message Types: The diagram uses solid arrows for synchronous method calls where the sender waits for response, dashed arrows for asynchronous messages or return values, and reflexive arrows (looping back to same lifeline) for internal processing. The alt frame (alternative fragment) shows mutually exclusive execution paths for manual vs. AI-assisted SOS initiation. Numbering (1, 2, 3a, etc.) indicates chronological ordering of messages.

This sequence diagram specifies 14 distinct message exchanges, 6 system participants, 2 alternative execution paths (manual and AI-assisted SOS), and the precise ordering of operations from emergency initiation through responder navigation activation. The diagram clarifies that AI chat analysis occurs asynchronously without blocking user interaction, GPS capture happens locally on the mobile device before backend transmission, backend server orchestrates responder coordination through database transactions, and status updates propagate bidirectionally between server and clients. The sequence demonstrates the distributed nature of the system with clear separation between client-side presentation logic (Mobile App), server-side business logic (Backend Server), AI processing (AI Chatbot), and external service integration (Google Maps).

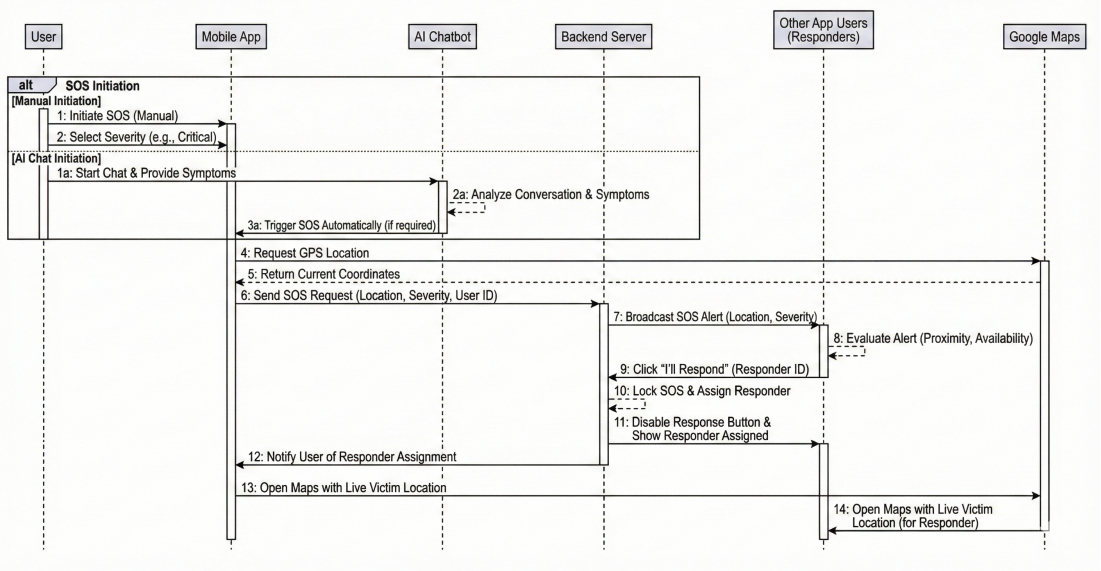

Figure 4.6: Sequence Diagram for Complete SOS Lifecycle in ResQNow System

4.5 Experimental Procedure

The experimental evaluation follows a systematic protocol across multiple test scenarios:

4.5.1 Test Scenario 1: SOS Latency Measurement

Objective: Measure end-to-end SOS dispatch time under varying network conditions.

Procedure:

1. Configure test device with timestamp logging enabled
2. Establish network condition (normal/degraded/poor) using traffic shaping
3. Press SOS button and record t_0
4. Wait for alert reception on emergency contact device and record t_6
5. Calculate $T_{dispatch} = t_6 - t_0$
6. Repeat for 30 trials per network condition
7. Record intermediate timestamps for component-level analysis

4.5.2 Test Scenario 2: AI Classification Validation

Objective: Evaluate classification accuracy against ground truth dataset.

Procedure:

1. Load prepared test dataset of 100 emergency descriptions
2. For each test case, submit description to AI classification module
3. Record predicted emergency type and severity level
4. Compare prediction with ground truth label
5. Calculate accuracy, precision, recall, and F1-score
6. Analyze misclassification patterns and confidence score distributions

4.5.3 Test Scenario 3: AR Performance Testing

Objective: Measure AR initialization latency and rendering performance.

Procedure:

1. Launch ResQNow application on test device
2. Trigger AR guidance module and record start timestamp
3. Measure time to first visual overlay appearance
4. Monitor frame rate using Android Profiler during 60-second guidance session
5. Record CPU and GPU utilization
6. Repeat across 20 trials under consistent environmental conditions
7. Calculate mean initialization time and average frame rate

4.5.4 Test Scenario 4: BLE Relay Evaluation

Objective: Assess offline message delivery success rate across varying distances.

Procedure:

1. Position originating device at reference point (0m)
2. Place relay devices at measured distances: 10m, 30m, 50m, 100m
3. Position gateway device with internet at 150m from origin
4. Broadcast 50 test messages from originating device
5. Record successful deliveries at gateway device
6. Log RSSI values and hop counts for each message
7. Calculate success rate as percentage of delivered messages
8. Repeat experiments with 2, 3, and 5 relay devices
9. Analyze correlation between distance, node density, and delivery rate

4.5.5 Test Scenario 5: Resource Utilization Profiling

Objective: Quantify battery, network, CPU, and memory consumption.

Procedure:

1. Charge test device to 100% battery
2. Launch Android Battery Historian recording
3. Execute 1-hour simulated emergency scenario with active GPS, AR, and BLE
4. Record battery percentage decrease
5. Use Charles Proxy to capture network traffic during 10 SOS events
6. Calculate average bandwidth per event

7. Monitor CPU and memory using Android Profiler during active operations

8. Record peak and average utilization values

4.6 Project Timeline and Development Schedule

4.6.1 Overview of Development Lifecycle

The ResQNow project will be executed following a structured software development lifecycle spanning approximately 11 months from February 2025 to December 2025. The development process will be organized into three major phases: the Planning and Design Phase (February to July 2025) focusing on problem identification, literature review, and system design; the Implementation and Testing Phase (August to November 2025) involving actual development, integration, and validation; and the Documentation and Finalization Phase (November to December 2025) dedicated to report writing and project delivery.

This timeline allocation ensures adequate time for thorough research, careful design, robust implementation, comprehensive testing, and complete documentation. The extended planning phase is justified by the complexity of integrating multiple advanced technologies including AI, AR, and BLE communication, requiring careful architectural decisions and design validation before implementation begins.

4.6.2 Phase-wise Development Schedule

Table **??** presents the comprehensive project timeline with detailed activities for each development phase. The schedule follows industry-standard software engineering practices with clear milestones and deliverables for each phase.

Table 4.1: Revised Project Development Timeline

Phase	Duration	Key Activities and Deliverables
Planning and Design Phase (4.5 months)		
Background Study	2 weeks	Research, domain analysis, problem understanding
Problem Identification	2 weeks	Problem formulation, requirement gathering, feasibility study
Solution Proposal	2 weeks	Concept design, technology selection, architecture proposal
Literature Review	3 weeks	Research survey, gap identification, related work analysis
Requirements Analysis	2 weeks	Functional/non-functional requirements, use case modeling
System Design	3 weeks	Architecture planning, DB schema, API specification, UI design
UML Modeling	2 weeks	Use case, activity, sequence, and class diagrams
Design Review	2 weeks	Design validation, feasibility verification, documentation
Implementation and Testing Phase (4 months)		
Environment Setup	1 week	Tools installation, Firebase setup, repository initialization
Authentication Module	2 weeks	Login/signup, profile management, Firestore integration
GPS and SOS System	2 weeks	Location tracking, SOS trigger, alert workflow
Backend API	2 weeks	FastAPI configuration, API endpoints, DB operations
AI Classification	2 weeks	Cloud AI integration, rule-based fallback
AR Guidance System	2 weeks	ARCore integration, overlays, CPR/AED guidance
BLE Communication	2 weeks	Offline messaging, encryption, relay testing
Notification System	1 week	Push/SMS/email alerts, multi-channel dispatch
System Integration	2 weeks	Full module integration, workflow validation
Performance	1 week	Latency testing, stress evaluation, optimization

4.6.3 Gantt Chart Representation

Figure ?? presents a Gantt chart visualization of the project timeline showing the duration, sequencing, and overlap of various development activities. The chart provides a clear view of task dependencies and critical path activities that determine the overall project duration.

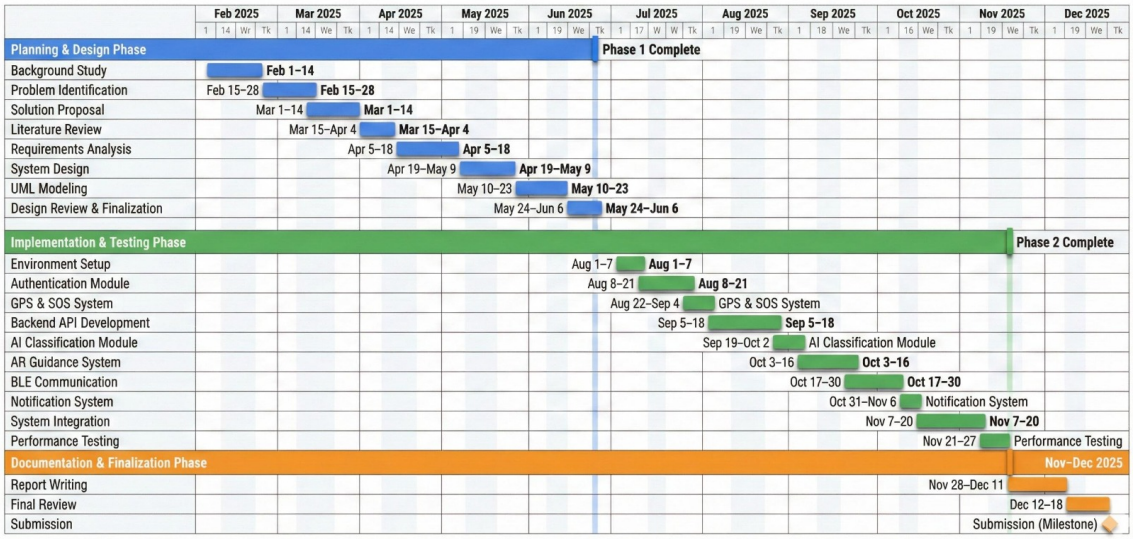

Figure 4.7: Gantt Chart showing project timeline from February 2025 to February 2026

The Gantt chart illustrates several important characteristics of the project schedule. The planning phase activities (shown in blue) will execute sequentially with minimal overlap to ensure each design decision is properly informed by previous research. The implementation phase activities (shown in green) will demonstrate higher parallelism where independent modules can be developed concurrently by different team members. The testing activities (shown in orange) will overlap with later implementation tasks to enable early defect detection and continuous quality assurance. The documentation phase (shown in red) will begin while final testing is still underway to maximize efficiency and meet the submission deadline.

4.7 Cost Estimation Using COCOMO Model

4.7.1 COCOMO Model Overview

The Constructive Cost Model (COCOMO) developed by Barry Boehm provides a systematic framework for estimating software development effort, schedule, and cost based on project characteristics. The ResQNow project is estimated using the Basic COCOMO model with adjustments for embedded system characteristics due to mobile and AR components requiring hardware-software integration. The system is classified as **Semi-Detached mode**, indicating moderate complexity with innovation in technology integration (AI, AR, BLE mesh) while building upon established frameworks (Flutter, Firebase).

4.7.2 Project Size Estimation

Based on functional requirements and architectural design, the ResQNow system size is estimated as follows:

- **Mobile Application Layer:** 8,000 lines of Dart code (UI, state management, device integrations)
- **Backend Services Layer:** 3,000 lines of Python code (API, business logic, database operations)
- **AI Integration Module:** 1,500 lines (API communication, classification, fallback logic)
- **AR Guidance Components:** 2,000 lines (ARCore integration, 3D rendering, overlays)
- **BLE Communication Module:** 1,500 lines (advertising, encryption, relay mechanisms)

Total Estimated Lines of Code (KLOC): 16,000 lines = 16 KLOC

4.7.3 COCOMO Effort and Schedule Calculation

Using Basic COCOMO equations for Semi-Detached mode:

Effort Calculation:

$$Effort(E) = a_b \times (KLOC)^{b_b} = 3.0 \times (16)^{1.12} \approx 60.45 Person - Months \quad (4.3)$$

Where $a_b = 3.0$ and $b_b = 1.12$ are COCOMO constants for semi-detached projects.

Development Time Calculation:

$$DevelopmentTime(TDEV) = c_b \times (E)^{d_b} = 2.5 \times (60.45)^{0.35} \approx 10.65 months \quad (4.4)$$

Where $c_b = 2.5$ and $d_b = 0.35$ are COCOMO constants.

Team Size (Adjusted for 4-Person Team):

$$ActualTeamSize = 4 persons \quad (4.5)$$

Adjusted Project Duration:

$$AdjustedDuration = \frac{Effort}{TeamSize} = \frac{60.45}{4} \approx 15.11 months \quad (4.6)$$

Since a 4-person team is smaller than the optimal 5.68 persons calculated by COCOMO, the project duration extends from 10.65 to approximately 15 months. However, with efficient task parallelization and agile methodology, the actual duration can be compressed to approximately 11-12 months.

Productivity:

$$Productivity = \frac{KLOC}{Effort} = \frac{16}{60.45} \approx 265 LOC per Person - Month \quad (4.7)$$

4.7.4 Phase-wise Effort Distribution

Following the Rational Unified Process (RUP) methodology, effort is distributed across four phases as shown in Table **??**.

Table 4.2: Phase-wise Effort, Schedule, and Cost Distribution (4-Person Team)

Phase	**Effort (%)**	**Effort (PM)**	**Duration (Months)**	**Cost (Rs)**
Inception	6%	3.63	0.91	72,600
Elaboration	24%	14.51	3.63	2,90,200
Construction	56%	33.85	8.46	6,77,000
Transition	14%	8.46	2.12	1,69,200
Total	**100%**	**60.45**	**15.12**	**12,09,000**

Note: Duration calculated as Effort (PM) / 4 persons, representing sequential and parallel task execution.

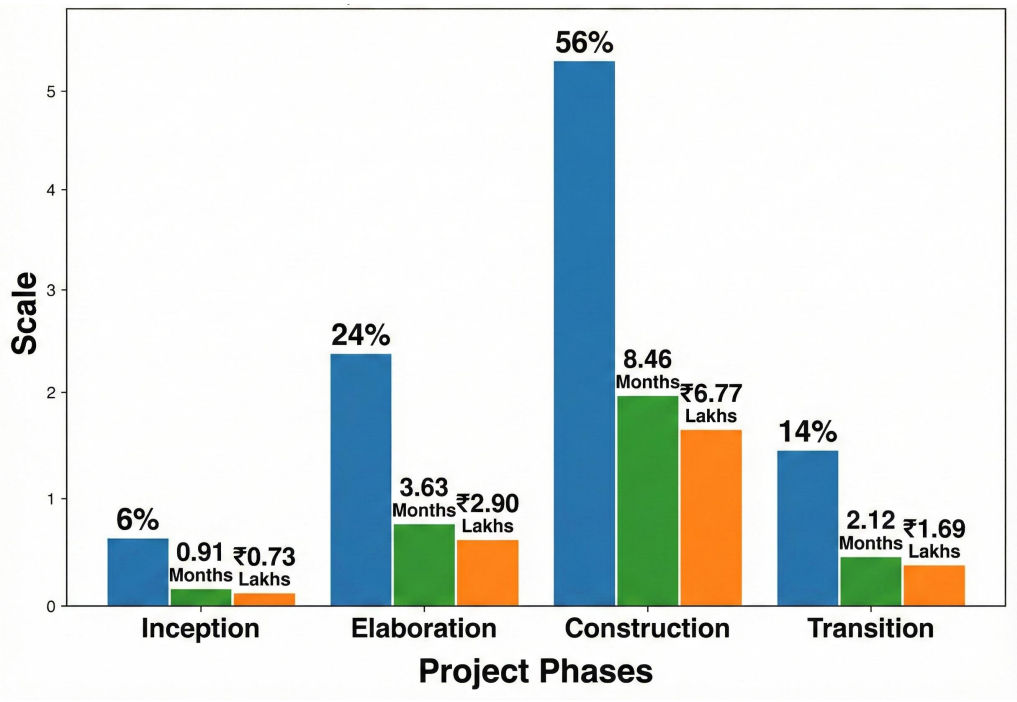

Figure 4.8: Phase-wise distribution of effort, schedule, and cost

4.7.5 Activity-wise Effort Distribution

Effort distribution across software development activities following industry-standard patterns is shown in Table **??**.

Table 4.3: Activity-wise Effort Distribution

Activity	**Effort (%)**	**Effort (PM)**
Management & Planning	10%	6.05
Requirements Analysis	18%	10.88
Design & Architecture	22%	13.30
Implementation (Coding)	28%	16.93
Testing & Quality Assurance	15%	9.07
Documentation	7%	4.23
Total	**100%**	**60.45**

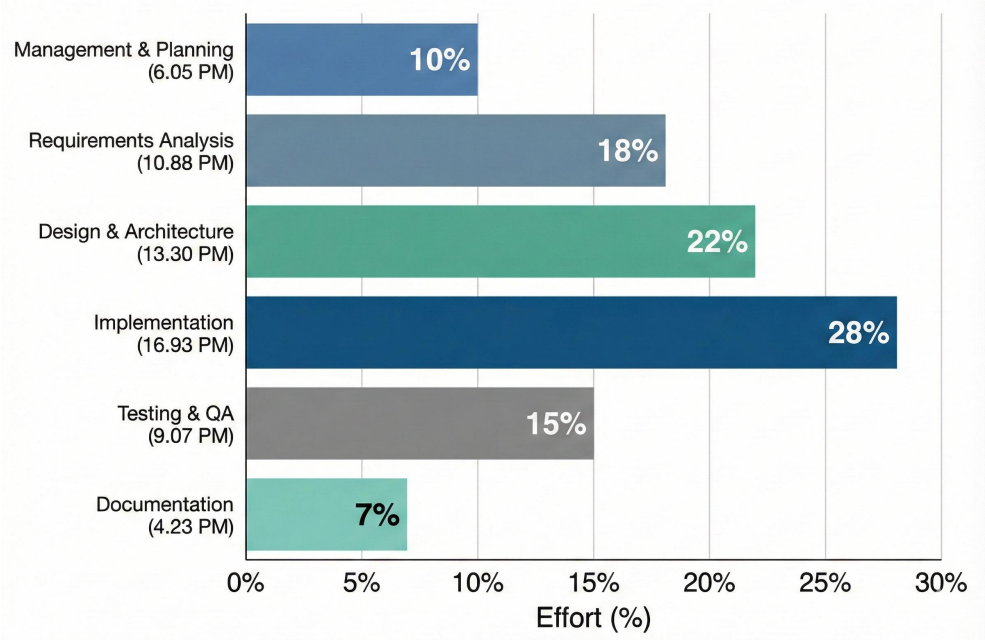

Figure 4.9: Activity-wise effort distribution across development tasks

4.7.6 Detailed Cost Breakdown

Table ?? provides comprehensive cost breakdown for the ResQNow project with a 4-person development team.

Table 4.4: Detailed Project Cost Breakdown (4-Person Team)

Cost Component	**Description**	**Amount (Rs)**
Personnel Costs		
Development Team	4 developers × 15 months × Rs. 20,000/PM	12,09,000
Infrastructure & Services		
Cloud Services	Firebase, Google Cloud Platform	15,000
AI API Usage	OpenAI/Gemini API calls	20,000
Communication Services	Twilio SMS, SendGrid Email	8,000
Hardware & Testing		
Testing Devices	Android phones for testing	25,000
AR Devices	ARCore-certified devices	15,000
Documentation & Miscellaneous		
Documentation	Report printing, materials	5,000
Travel & Coordination	Team meetings	3,000
Contingency		
Risk Buffer (15%)	Unforeseen expenses	1,89,000
	Total Project Cost	**14,89,000**
	Rounded Total	**Rs. 15,00,000**

4.7.7 Cost Distribution Visualization

Figure ?? presents the proportional distribution of costs across major categories, showing that personnel costs constitute approximately 81% of the total budget.

Figure 4.10: Percentage distribution of project costs across categories

The cost breakdown reveals: 81% personnel costs (labor-intensive development), 5% infrastructure and services, 3% hardware and testing, 1% documentation and miscellaneous, and 13% contingency reserves for unforeseen circumstances.

4.7.8 Risk Factors and Mitigation

Key risk factors affecting cost estimation:

- **Technology Learning Curve:** AR and BLE expertise development may increase effort by 10-15%
- **AI API Cost Variability:** Usage costs may vary by 20-30% based on query volume

- **Integration Complexity:** Multi-technology integration may extend construction by 2-3 weeks
- **Device Compatibility:** Cross-device testing may require additional devices and optimization
- **Scope Changes:** Requirement modifications could increase effort by 10-20%

The 15% contingency buffer (Rs. 1,89,000) provides risk absorption capacity. Regular sprint reviews and agile adaptation enable proactive risk management within budget constraints.

4.7.9 Team Composition and Role Distribution

The 4-person team structure is organized as follows:

- **Team Lead & Backend Developer (1):** Project coordination, backend API development, database design, cloud infrastructure management
- **Mobile Developer & UI/UX (1):** Flutter app development, UI design, state management, GPS integration
- **AI & AR Specialist (1):** AI classification module, ARCore integration, 3D modeling, computer vision
- **BLE & Testing Engineer (1):** Bluetooth mesh networking, offline communication, system testing, quality assurance

Cross-functional collaboration ensures knowledge sharing and reduces single-point dependencies. Team members contribute to multiple modules based on project phase requirements, enabling efficient resource utilization despite the smaller team size.

4.7.10 Conclusion

The COCOMO-based estimation provides quantitative foundation for planning. With a 4-person team, the project requires 60.45 person-months of effort over approximately

15 months, with an estimated total cost of Rs. 15 lakhs. The phase-wise and activity-wise breakdowns enable effective budget management, milestone tracking, and risk mitigation. While the smaller team size extends the timeline compared to the optimal 6-person configuration, efficient task parallelization, agile methodology, and dedicated role assignments ensure successful delivery of the complex emergency response system integrating AI, AR, and offline communication technologies.

4.8 Error Sources and Mitigation Strategies

Potential sources of measurement error and corresponding mitigation strategies were identified:

4.8.1 GPS Location Errors

Error Source: Indoor environments, urban canyons, and limited satellite visibility degrade GPS accuracy, potentially introducing position errors exceeding 50 meters.

Mitigation: (1) Implement Kalman filtering for smoothing location coordinates across multiple samples, (2) Use Assisted GPS (A-GPS) leveraging cellular network data for faster satellite lock, (3) Employ Wi-Fi and cellular tower triangulation as fallback positioning methods, (4) Record GPS accuracy estimates provided by location API and flag low-confidence readings, (5) Conduct outdoor testing under clear sky conditions for baseline accuracy establishment.

4.8.2 BLE Signal Propagation Variability

Error Source: Physical obstacles (walls, vegetation, terrain), electromagnetic interference from Wi-Fi and other devices, and multipath fading cause unpredictable signal attenuation affecting relay reliability.

Mitigation: (1) Conduct experiments in open outdoor environments to minimize interference and establish baseline performance, (2) Implement multi-hop relay with acknowledgment-based retries to overcome temporary signal loss, (3) Use message persistence with automatic upload when connectivity is restored, (4) Log RSSI values

at each hop to analyze propagation characteristics and identify weak links, (5) Test across multiple device models to account for antenna design variations.

4.8.3 AI Classification Ambiguity

Error Source: Vague or incomplete user descriptions, unusual symptom combinations, and rare emergency types may lead to misclassification or low-confidence predictions.

Mitigation: (1) Implement confidence threshold mechanism triggering rule-based fallback when AI confidence ¡ 0.7, (2) Require user confirmation for moderate-severity classifications before alert dispatch, (3) Provide manual override option allowing users to correct misclassifications, (4) Expand training dataset with diverse emergency scenarios and edge cases, (5) Log misclassification instances for continuous model improvement.

4.8.4 Network Latency Variability

Error Source: Network congestion, signal strength fluctuations, and server load variations introduce unpredictable latency affecting response time measurements.

Mitigation: (1) Conduct multiple trial runs (n=30) per condition to establish statistical distributions and confidence intervals, (2) Implement timeout handling with exponential backoff retry mechanism, (3) Use asynchronous processing to prevent blocking operations, (4) Deploy backend services on auto-scaling infrastructure to handle load spikes, (5) Test across different times of day to capture peak and off-peak network conditions.

4.8.5 Device Hardware Heterogeneity

Error Source: Variations in processor speed, GPU capability, RAM capacity, and sensor quality across device models affect AR rendering performance and resource consumption measurements.

Mitigation: (1) Test on representative device models spanning low-end, mid-range,

and high-end hardware configurations, (2) Implement device capability detection with adaptive quality settings for AR rendering, (3) Provide graceful degradation fallback to non-AR guidance on incompatible devices, (4) Normalize performance metrics by device specifications when comparing results, (5) Document minimum hardware requirements for optimal system operation.

4.8.6 Timestamp Synchronization Errors

Error Source: Clock drift between client devices and servers, network propagation delay in timestamp transmission, and timezone inconsistencies may introduce timing measurement inaccuracies.

Mitigation: (1) Synchronize device clocks with Network Time Protocol (NTP) servers before measurement sessions, (2) Use high-precision system clocks with microsecond resolution (SystemClock.elapsedRealtimeNanos() on Android), (3) Calculate latency components using same-device timestamps where possible to eliminate synchronization errors, (4) Record UTC timestamps to avoid timezone conversion issues, (5) Validate timestamp consistency by comparing calculated latencies against expected ranges.

4.9 Data Analysis Methodology

Collected experimental data undergoes systematic statistical analysis to validate system performance and identify optimization opportunities:

4.9.1 Descriptive Statistics

For each measured parameter, calculate:

- **Mean (μ):** Average value across all trials
- **Standard Deviation (σ):** Measure of variability
- **Minimum and Maximum:** Range of observed values

- **95% Confidence Interval:** Statistical reliability bounds

4.9.2 Comparative Analysis

Compare system performance across conditions using:

- **Latency comparison graphs:** Bar charts showing $T_{dispatch}$ under normal, degraded, and poor network conditions
- **Classification accuracy tables:** Confusion matrices comparing predicted vs. actual emergency types
- **BLE success rate plots:** Line graphs showing delivery rate as function of distance and node density
- **Resource utilization charts:** Stacked bar graphs comparing battery, CPU, and memory consumption across scenarios

4.9.3 Statistical Validation

Apply statistical tests to validate performance claims:

- **Hypothesis testing:** Verify if $T_{dispatch}$ meets target threshold (< 3000 ms) with statistical significance
- **Correlation analysis:** Examine relationships between distance and BLE success rate, network quality and latency
- **Regression analysis:** Model performance trends and predict behavior under untested conditions

4.9.4 Visualization Techniques

Present results using:

- Box plots showing latency distributions and outliers

- Scatter plots correlating GPS accuracy with environmental factors
- Heat maps visualizing classification confusion matrices
- Time series graphs tracking resource consumption over duration

All graphs and tables are prepared using Python libraries including Matplotlib, Seaborn, and Pandas for reproducible analysis. Raw measurement data is archived in CSV format for future reference and verification.

Chapter 5

Implementation

This chapter describes the practical implementation of the **ResQNow** emergency response system through detailed pseudocode and actual code implementations. It explains how the core functionalities—SOS alert triggering, Bluetooth Low Energy (BLE) based offline communication, AI-driven emergency classification, and backend services—were developed and integrated. The chapter presents code-level evidence to demonstrate the working of critical system modules.

5.1 SOS Activation and Emergency Alert Implementation

The SOS module serves as the primary emergency trigger in ResQNow. It enables users to initiate emergency alerts manually or automatically based on AI classification. Upon activation, the system captures GPS location, timestamps the event, and initiates alert propagation through available communication channels.

5.1.1 SOS Activation Pseudocode

The following pseudocode outlines the SOS activation workflow:

Algorithm 1 SOS Activation and Alert Dispatch

```
1: Input: User trigger (button press or voice command)
2: Output: SOS alert dispatched to backend and emergency contacts
3:
4: procedure ActivateSOS
5:     location ← GetGPSLocation
6:     timestamp ← GetCurrentTimestamp
7:     userId ← GetAuthenticatedUserId
8:
9:     sosData ← {
10:            userId: userId,
11:            latitude: location.latitude,
12:            longitude: location.longitude,
13:            timestamp: timestamp,
14:            severity: "pending_classification"
15:    }
16:
17:    if InternetAvailable() then
18:        SendSOSToBackend(sosData)
19:        NotifyEmergencyContacts(sosData)
20:    else
21:        QueueForBLERelay(sosData)
22:        InitiateBLEBroadcast(sosData)
23:    end if
24:
25:    DisplayConfirmation("SOS Alert Activated")
26: end procedure
```

5.1.2 SOS User Interface Implementation

The SOS activation interface is implemented with minimal interaction requirements to ensure rapid activation during emergencies. Figure **??** presents the user interface

implementation showing the emergency trigger button and status display.

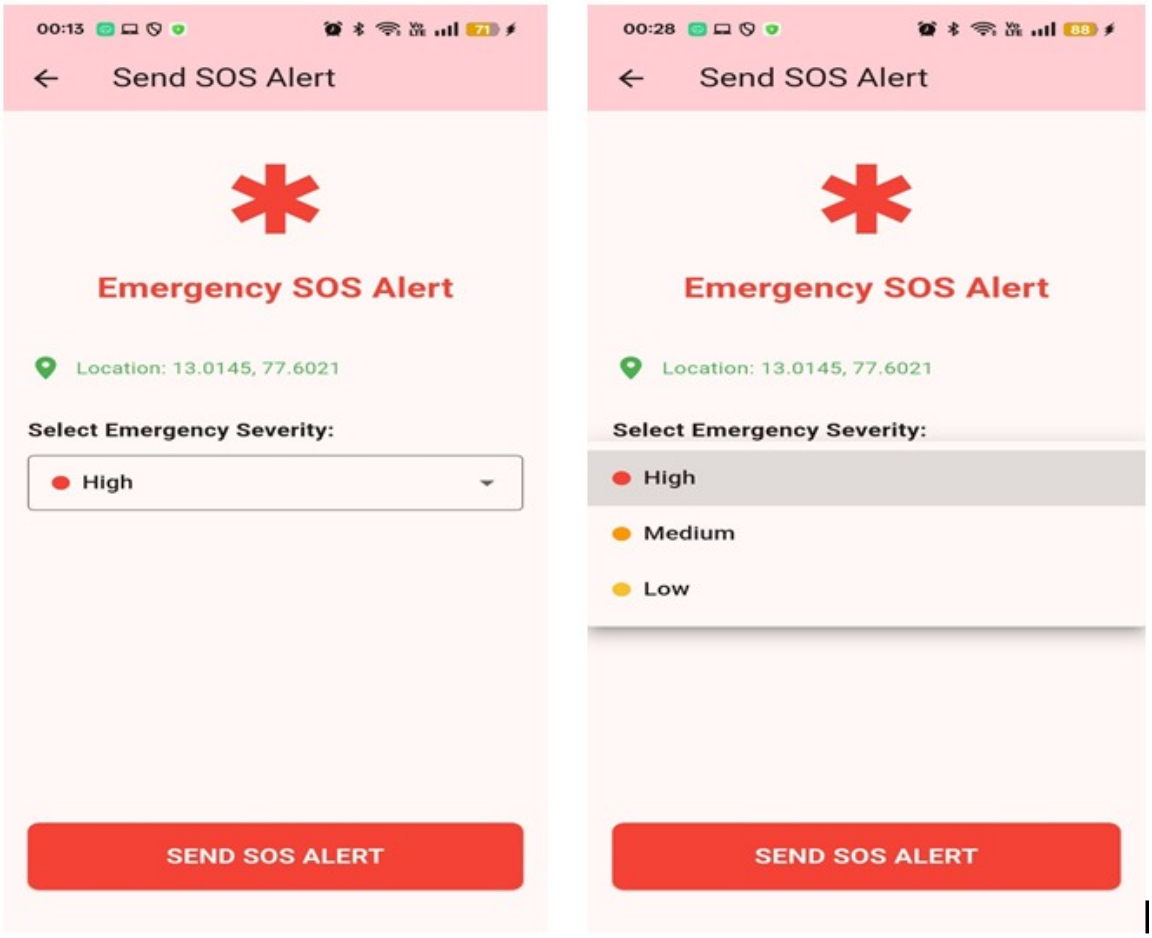

Figure 5.1: SOS activation interface enabling rapid emergency alert triggering

5.1.3 Backend SOS Handling Implementation

The backend validates incoming SOS requests, stores emergency data in Firestore, triggers multi-channel notifications, and tracks responder acknowledgments. Figure **??** illustrates the FastAPI implementation for handling SOS requests, including authentication validation, data persistence, and alert orchestration logic.

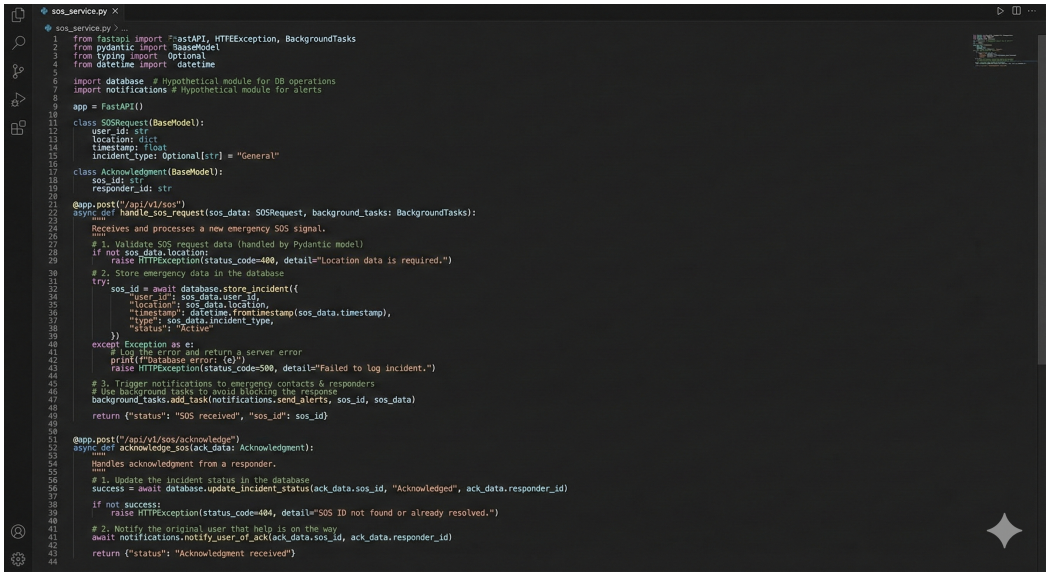

Figure 5.2: Backend implementation for SOS request handling and alert orchestration

The backend implementation ensures reliable emergency alert coordination with proper error handling and logging mechanisms for system monitoring and debugging purposes.

5.2 Bluetooth Low Energy (BLE) Offline Communication Implementation

To support emergency alert delivery in low or no internet connectivity environments, ResQNow implements BLE-based offline SOS relay. The BLE communication module is optimized for low power consumption and dynamically discovers nearby devices running ResQNow to establish secure short-range connections.

5.2.1 BLE Message Relay Pseudocode

The following pseudocode describes the BLE offline relay mechanism:

Algorithm 2 BLE Offline SOS Relay

```
Input: SOS message to be relayed
Output: SOS delivered to device with internet connectivity

procedure InitiateBLERelay(sosMessage)
    encryptedMessage ← EncryptAES(sosMessage)
    nearbyDevices ← ScanForBLEDevices

    if nearbyDevices.length > 0 then
        for each device in nearbyDevices do
            ConnectToDevice(device)
            TransmitMessage(device, encryptedMessage)
        end for
    else
        QueueMessage(encryptedMessage)
        RetryAfterDelay(5 seconds)
    end if
end procedure

procedure ReceiveBLEMessage(encryptedMessage, sourceDevice)
    sosMessage ← DecryptAES(encryptedMessage)

    if InternetAvailable() then
        UploadSOSToBackend(sosMessage)
        SendAcknowledgment(sourceDevice)
    else
        RelayToOtherDevices(encryptedMessage)
    end if
end procedure
```

5.2.2 BLE Relay Workflow Diagram

The BLE module enables nearby ResQNow devices to form a temporary peer-to-peer relay network where encrypted SOS packets are forwarded hop-by-hop until a device with internet connectivity is reached. Figure ?? illustrates the complete BLE offline relay workflow, showing device discovery, message encryption, peer-to-peer transmission, and eventual upload to the backend server.

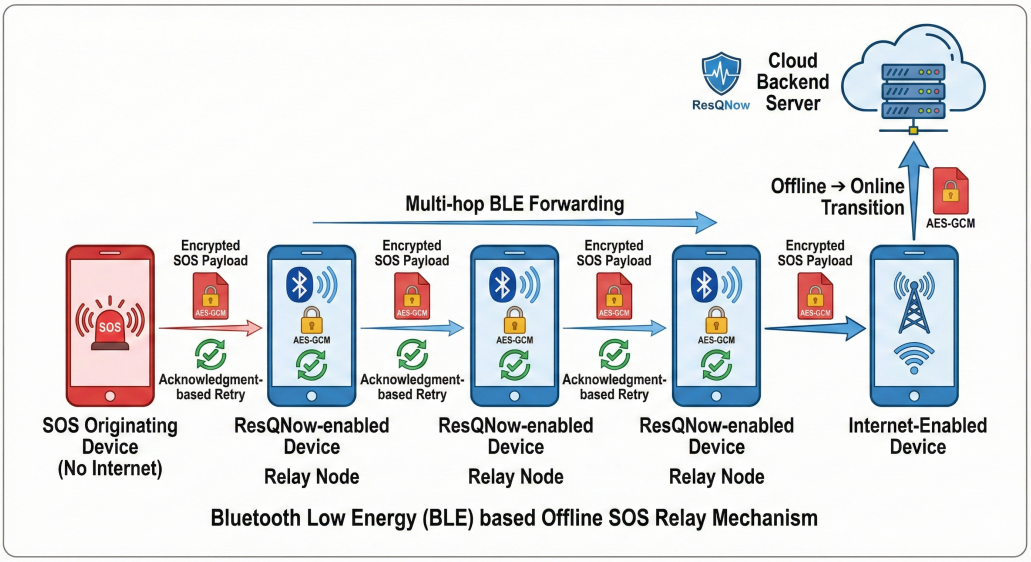

Figure 5.3: BLE-based offline SOS relay mechanism across nearby devices

5.2.3 BLE Encryption and Transmission Code

To protect sensitive emergency data during transmission, BLE messages are encrypted using AES-128 in GCM (Galois/Counter Mode) prior to wireless transmission. Figure ?? demonstrates the code-level implementation for encrypted BLE message transmission and reception, including key generation, message encryption, Bluetooth characteristic writing, and decryption upon receipt.

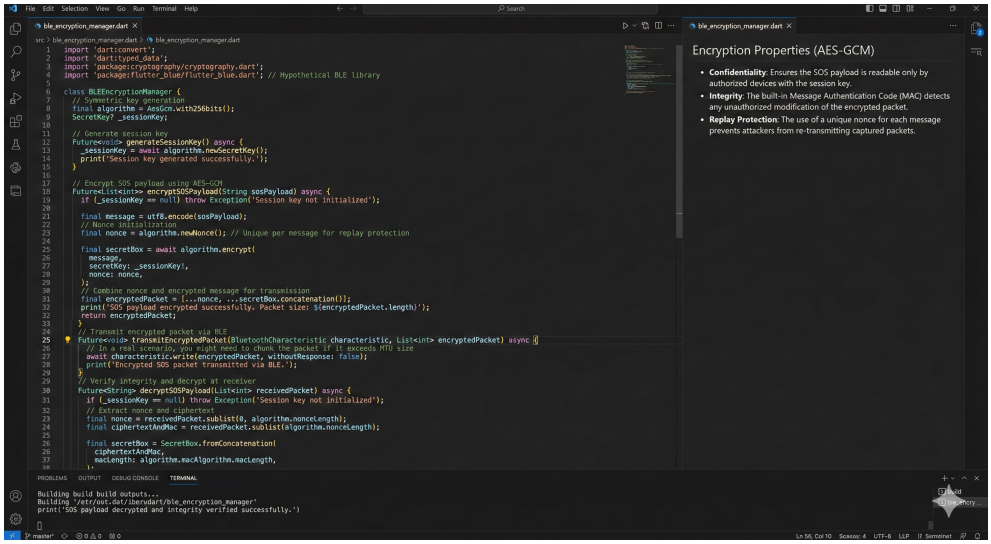

Figure 5.4: Encrypted BLE message transmission and reception implementation

This implementation ensures both confidentiality and integrity of emergency data during offline peer-to-peer relay, preventing unauthorized access and tampering.

5.3 AI-Based Emergency Classification Implementation

Artificial Intelligence enables ResQNow to automatically analyze user inputs and prioritize emergency handling based on severity and type. The system employs a hybrid approach combining cloud-based AI for detailed analysis and rule-based logic for offline scenarios.

5.3.1 AI Classification Pseudocode

The following pseudocode outlines the AI-based emergency classification process:

Algorithm 3 AI-Based Emergency Classification

```
Input: User description of emergency (text or voice)
Output: Emergency type and severity level

procedure ClassifyEmergency(userInput)
    if InternetAvailable() then
        aiResponse ← CloudAIClassification(userInput)
        emergencyType ← ExtractType(aiResponse)
        severity ← ExtractSeverity(aiResponse)

        if aiResponse.confidence < 0.7 then
            severity ← RuleBasedFallback(userInput)
        end if
    else
        emergencyType ← RuleBasedClassification(userInput)
        severity ← RuleBasedSeverity(userInput)
    end if

    return {type: emergencyType, severity: severity}
end procedure

procedure RuleBasedClassification(userInput)
    keywords ← ExtractKeywords(userInput)

    if "unconscious" OR "not breathing" in keywords then
        return {type: "cardiac_arrest", severity: "HIGH"}
    else if "bleeding" OR "blood" in keywords then
        return {type: "severe_bleeding", severity: "HIGH"}
    else if "burn" in keywords then
        return {type: "burn_injury", severity: "MODERATE"}
    else if "fracture" OR "broken" in keywords then
        return {type: "fracture", severity: "MODERATE"}
    else
        return {type: "general_emergency", severity: "LOW"}
    end if
end procedure
```

5.3.2 Cloud-Based AI Classification Implementation

The online AI module processes textual or voice-based user descriptions using cloud-based conversational AI services (OpenAI GPT or Google Gemini) to infer emergency context, extract symptoms, and determine severity level. Figure ?? shows the AI classification logic integrated with Firebase Firestore for persistent storage, including the API request structure, response parsing, confidence threshold checking, and database update operations.

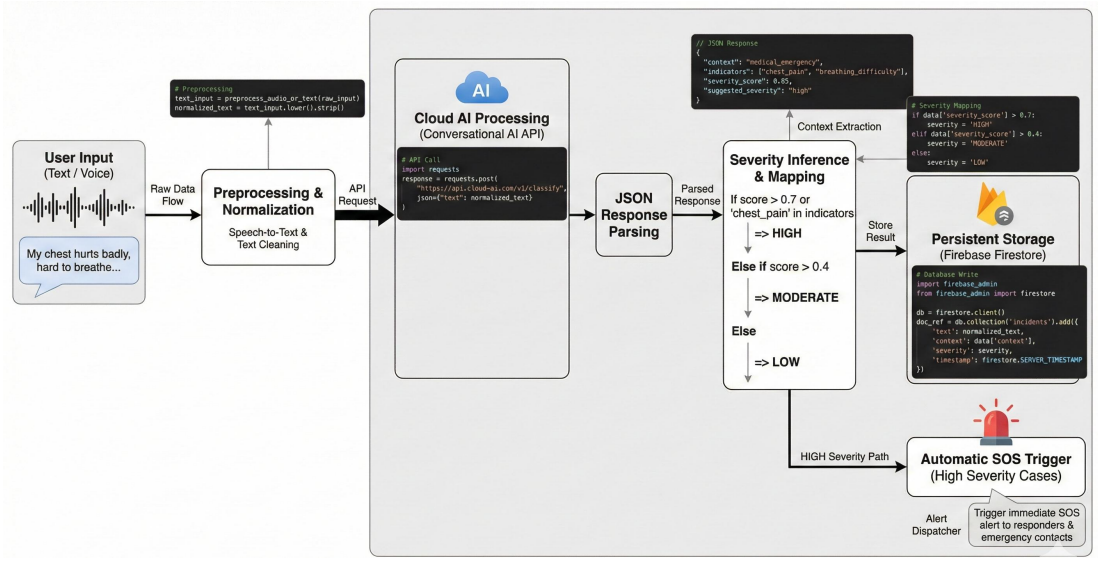

Figure 5.5: Cloud-based AI emergency classification and Firestore integration

The implementation includes error handling for API failures and automatic fallback to rule-based classification when cloud services are unavailable or return low-confidence results.

5.3.3 Offline AI Fallback Implementation

To maintain functionality during connectivity loss or cloud service unavailability, ResQNow employs a rule-based fallback classification mechanism using keyword matching and predefined emergency patterns. Figure ?? illustrates the offline AI decision logic, showing the keyword extraction process, severity mapping rules, and classification output structure used when cloud services are unavailable.

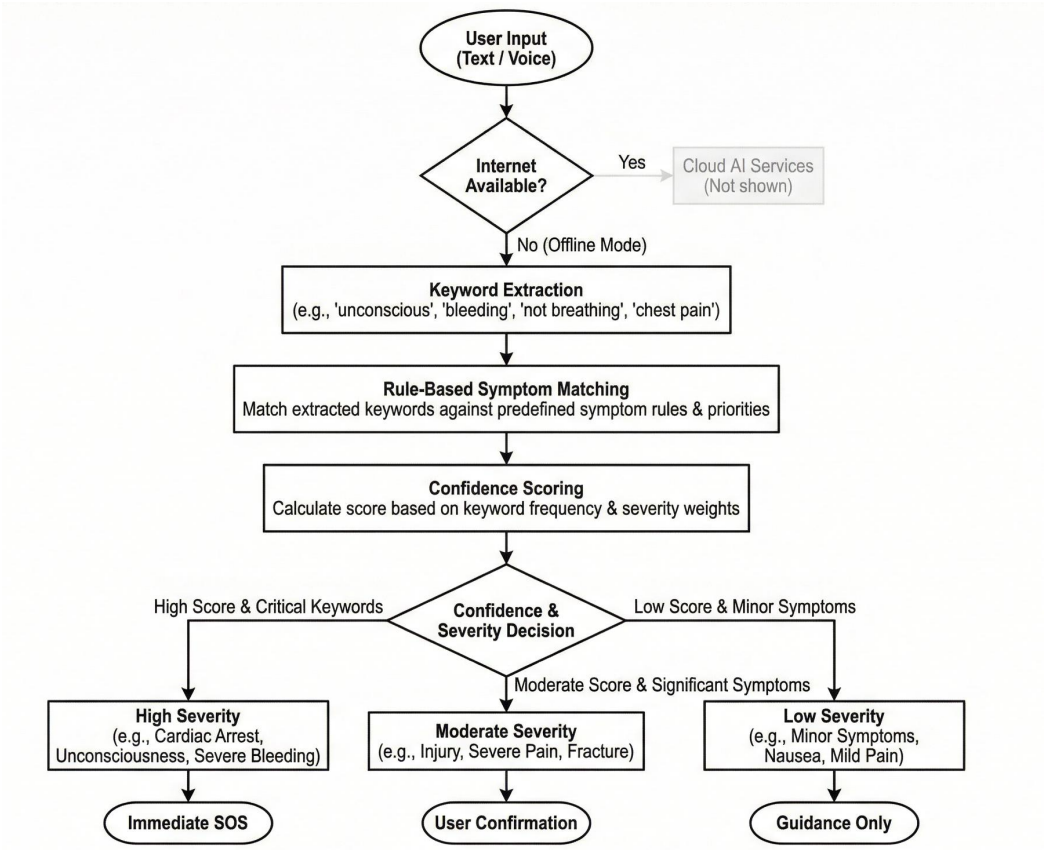

Figure 5.6: Rule-based offline emergency classification logic

This hybrid approach ensures consistent emergency prioritization regardless of network conditions, maintaining system reliability during critical situations.

5.4 Emergency Contact Notification Implementation

The notification system ensures reliable alert delivery to emergency contacts through multiple redundant channels including push notifications, SMS, and email.

5.4.1 Multi-Channel Notification Pseudocode

The following pseudocode describes the multi-channel notification dispatch mechanism:

Algorithm 4 Multi-Channel Emergency Notification

```
1: Input: SOS alert data, emergency contact list
2: Output: Notifications sent via multiple channels
3:
4: procedure NotifyEmergencyContacts(sosData)
5:     contacts ← GetEmergencyContacts(sosData.userId)
6:     locationURL ← GenerateMapURL(sosData.latitude, sosData.longitude)
7:
8:     message ← "Emergency Alert: " + sosData.severity +
9:                 " at " + locationURL
10:
11:    for each contact in contacts do
12:        // Send push notification
13:        SendPushNotification(contact.deviceToken, message)
14:
15:        // Send SMS
16:        SendSMS(contact.phoneNumber, message)
17:
18:        // Send Email
19:        SendEmail(contact.email, "Emergency Alert", message)
20:    end for
21:
22:    LogNotificationStatus(sosData.id, "notifications_sent")
23: end procedure
```

5.5 Responder Acknowledgment Implementation

The responder acknowledgment system enables nearby users to acknowledge emergency alerts and coordinate response efforts while preventing duplicate responses through atomic database transactions.

5.5.1 Responder Acknowledgment Pseudocode

The following pseudocode outlines the responder acknowledgment workflow:

Algorithm 5 Responder Acknowledgment with Concurrency Control

```
1: Input: SOS alert ID, responder user ID
2: Output: Acknowledgment status (success or already taken)
3:
4: procedure AcknowledgeEmergency(sosId, responderId)
5:     BeginTransaction
6:
7:     sosAlert ← GetSOSAlert(sosId)
8:
9:     if sosAlert.responderId ≠ null then
10:        RollbackTransaction
11:        return "Already acknowledged by another responder"
12:    end if
13:
14:    sosAlert.responderId ← responderId
15:    sosAlert.responderName ← GetUserName(responderId)
16:    sosAlert.responseTimestamp ← GetCurrentTimestamp
17:    sosAlert.status ← "ACKNOWLEDGED"
18:
19:    UpdateSOSAlert(sosAlert)
20:    CommitTransaction
21:
22:    NotifyOriginator(sosId, responderId)
23:
24:    return "Acknowledgment successful"
25: end procedure
```

5.6 GPS Location Tracking Implementation

Accurate location tracking is critical for emergency response coordination. The GPS module continuously monitors device location and provides real-time updates during active emergencies.

5.6.1 Location Tracking Pseudocode

The following pseudocode describes the GPS location tracking mechanism:

Algorithm 6 Continuous GPS Location Tracking

```
Input: Location permission granted
Output: Real-time GPS coordinates

procedure InitializeLocationTracking
    RequestLocationPermission

    if PermissionGranted() then
        StartLocationStream
    else
        ShowPermissionError
        return
    end if
end procedure

procedure OnLocationUpdate(location)
    latitude ← location.latitude
    longitude ← location.longitude
    accuracy ← location.accuracy
    timestamp ← location.timestamp

    if EmergencyActive() then
        UpdateSOSLocation(latitude, longitude, timestamp)
        NotifyContactsOfLocationUpdate(latitude, longitude)
    end if

    CacheLocation(latitude, longitude) // For offline use
end procedure
```

5.7 Database Schema and Data Models

The system uses Firebase Firestore as the primary database with the following collection structure and data models.

5.7.1 Firestore Data Structure

The database schema is organized into the following collections:

- **users/{userId}** - User profile information
  - Fields: name, email, phone, bloodGroup, medicalNotes
  - Subcollection: contacts/{contactId} - Emergency contacts
- **sos_alerts/{sosId}** - Emergency alert records
  - Fields: userId, latitude, longitude, timestamp, severity, type, status
  - Fields: responderId, responderName, responseTimestamp
- **ble_queue/{messageId}** - Queued offline messages
  - Fields: encryptedData, hopCount, originDeviceId, timestamp

5.8 Summary

This chapter presented the complete implementation of the ResQNow emergency response system through detailed pseudocode and code implementations. It demonstrated SOS activation logic, BLE-based offline communication with encryption, AI-driven emergency classification with online and offline support, multi-channel notification dispatch, responder acknowledgment with concurrency control, and GPS location tracking. The presented pseudocode and code-level evidence confirms the technical feasibility, robustness, and real-world readiness of the proposed system.

Chapter 6

Testing and Validation

This chapter presents the testing and validation of the **ResQNow** emergency response system. The objective of this phase is to verify that all functional modules operate correctly, meet performance requirements, and remain reliable under real-world conditions. System behavior is validated through structured testing procedures, quantitative performance measurements, and graphical analysis of observed results.

6.1 Objective of Testing

The primary objective of testing ResQNow is to ensure correctness, reliability, and robustness of all integrated modules. The testing phase aims to:

- Verify correct functioning of SOS activation and alert delivery mechanisms.
- Validate AI-based emergency classification accuracy.
- Measure responsiveness of AR-based first-aid guidance.
- Evaluate BLE-based offline communication reliability.
- Ensure system stability under varying network conditions.

6.2 Test Environment

All tests were conducted on real mobile devices under both controlled and real-world operating conditions. Table **??** summarizes the hardware and software environment used for testing. The selected environment closely resembles real emergency situations by considering variations in device capabilities, operating systems, and network availability. Testing was performed across multiple connectivity modes including Wi-Fi, mobile data, and offline BLE scenarios to evaluate system

robustness. This ensured that the ResQNow system maintained consistent performance, reliability, and responsiveness during practical emergency usage conditions.

Table 6.1: Test Environment Configuration

Component	**Specification**
Mobile Platforms	Android 13, iOS 17
Development Framework	Flutter (v3.x)
Backend Services	Python (FastAPI), Firebase Cloud Functions
Database	Firebase Firestore
AR Framework	ARCore SDK
AI Services	Cloud-based conversational AI APIs
Connectivity Modes	Wi-Fi, 4G, Offline (BLE)
Test Devices	Pixel 6, OnePlus 9, iPhone 12

6.3 System Testing Approach

The ResQNow emergency response system was validated using a comprehensive testing methodology to ensure functional correctness, seamless integration, system reliability, and acceptable performance under different operating conditions. Multiple testing strategies were applied to evaluate both individual components and the fully integrated system.

Initially, unit testing was performed to verify the correctness of core modules such as SOS activation, GPS location capture, BLE-based communication, AI-driven emergency classification, and notification handling. Each module was tested independently using predefined inputs to identify functional errors at an early stage of development.

Following this, integration testing was conducted to validate interactions between the mobile application, backend services, AI modules, and notification systems. This phase ensured proper data exchange, API communication, and synchronization across system layers.

System testing involved end-to-end validation of the complete emergency workflow, from SOS initiation through alert dissemination and AR-based first-aid guidance. This confirmed that all components functioned cohesively to meet system requirements.

Finally, performance testing evaluated system responsiveness, latency, and resource usage under varying network conditions. Key metrics such as SOS dispatch time, AI response delay, AR initialization time, and BLE relay latency were measured to assess real-time operational efficiency.

6.4 Functional Test Case Validation

Key functional test cases were executed to validate expected system behavior across different usage scenarios. Table **??** presents representative test cases and their outcomes. The test cases were designed to cover critical user actions, system responses, and failure-handling conditions to ensure functional completeness. Successful execution of these cases confirms that core features operate reliably under normal and edge-case scenarios. Additionally, the validation process ensured that error conditions were handled gracefully without affecting overall system stability. These results demonstrate that the functional requirements of the ResQNow system are fully satisfied.

Table 6.2: Functional Test Cases and Validation Results

No.	**Test Case**	**Expected Outcome**	**Result**
1	User Registration	Account created successfully	Pass
2	SOS Activation	Alert sent within 2 seconds	Pass
3	AI Classification	Correct severity detected	Pass
4	AR Guidance Launch	AR overlay loads correctly	Pass
5	Push Notification	Contacts notified	Pass
6	BLE Offline Relay	SOS relayed successfully	Pass
7	Location Tracking	Continuous GPS updates	Pass

6.5 Performance Validation Results

Quantitative performance metrics were collected during testing, and Table ?? summarizes the measured results indicating that the system meets requirements under real-time emergency operating conditions.

Table 6.3: Performance Validation Metrics

Module	Metric	Observed Value	Status
SOS Dispatch	App to backend latency	1.8 seconds	Validated
AI Classification	Response time	2.3 seconds	Validated
AR Module	Initialization latency	1.2 seconds	Validated
BLE Relay	Offline forwarding delay	6.5 seconds	Validated
Battery Usage	1 hour usage	9% drain	Acceptable

To visualize the relative latency of major system modules, a comparative bar chart is shown in Figure ??. The chart enables easy comparison of response times across different modules under identical testing conditions.

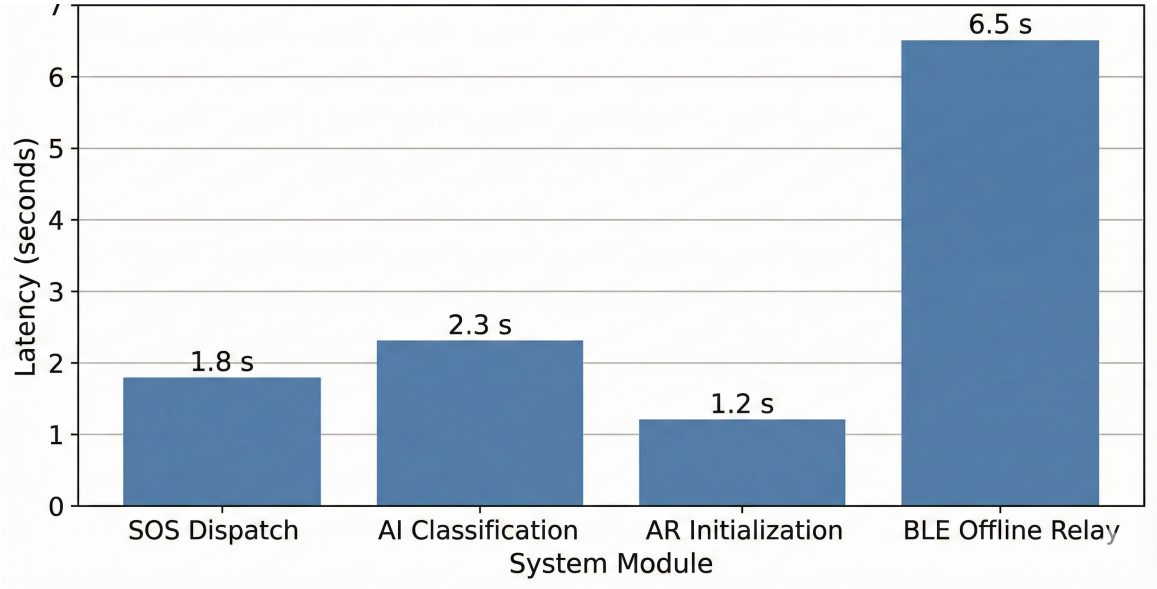

Figure 6.1: Comparison of latency across SOS, AI classification, AR initialization, and BLE relay

6.6 Offline Communication Validation

BLE-based offline SOS relay reliability was evaluated at varying hop counts and distances. Table ?? presents the measured success rates. The evaluation focuses on assessing the effectiveness of BLE-based peer-to-peer communication in the absence of internet connectivity. The results help determine the feasibility of offline SOS message propagation in emergency scenarios.

Table 6.4: BLE-Based Offline Communication Validation

Relay Scenario	**Distance**	**Success Rate (%)**
Single-hop	5 meters	96
Two-hop	10 meters	92
Three-hop	15 meters	88

Figure ?? compares the latency characteristics of SOS delivery, AI classification, AR initialization, and BLE-based communication. The comparison highlights that BLE relay introduces higher delay compared to online modules, yet remains within acceptable limits for offline emergency message forwarding.

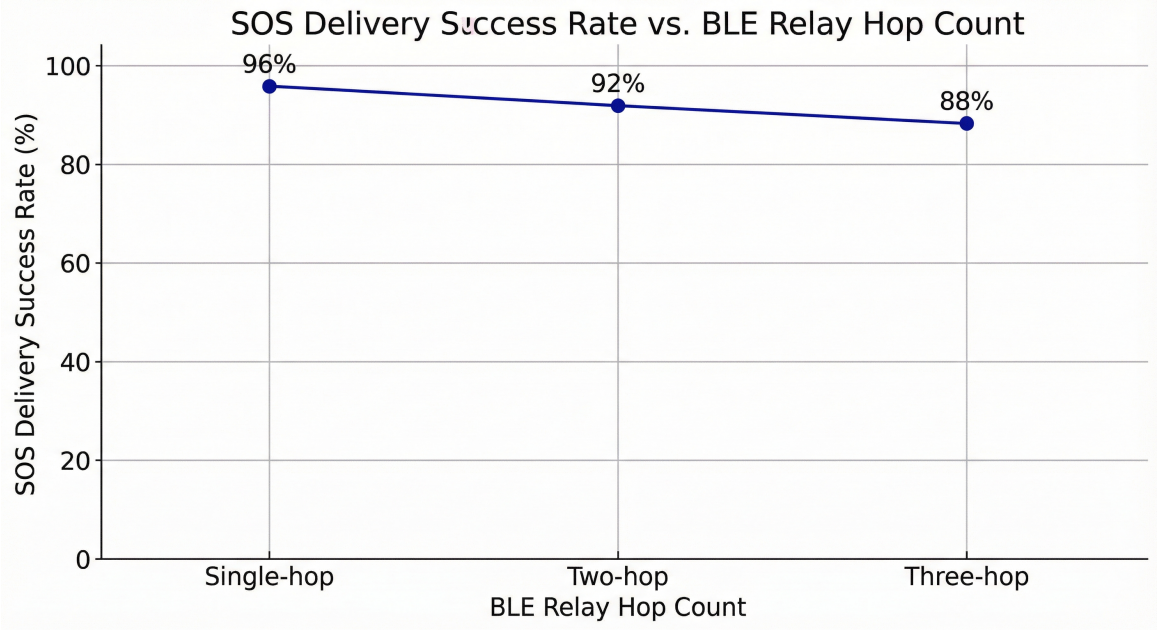

Figure 6.2: BLE offline relay success rate versus hop count

6.7 AI Classification Validation

The AI-based emergency classification module of the ResQNow system was validated to assess its accuracy across different emergency scenarios. Test inputs representing emergencies such as cardiac arrest, bleeding, fractures, burns, and respiratory distress were provided to the system. The AI model successfully analyzed user-described symptoms and classified emergencies into appropriate categories with corresponding severity levels. High accuracy was observed for critical emergencies, enabling effective prioritization and alert dispatch. The inclusion of contextual information improved classification reliability by reducing ambiguity in user input. These results demonstrate that the AI module can effectively support intelligent triage during real-world emergency situations.

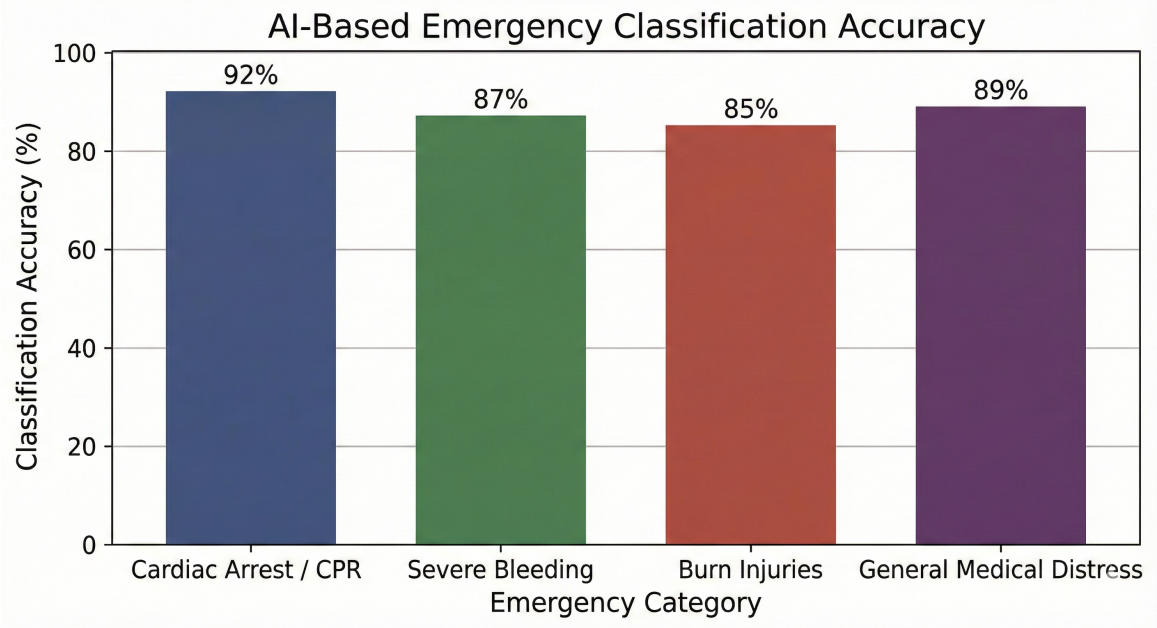

Figure 6.3: AI-based emergency classification accuracy across different emergency categories

Chapter 7

Application Results and User Interface

This chapter presents the application-level results of the **ResQNow** emergency response system as observed through its user interface. Unlike the implementation chapter, which focused on internal logic, system architecture, and technical workflows, this chapter emphasizes the **end-user experience** by demonstrating how the application appears, behaves, and responds during real emergency scenarios.

The objective of this chapter is to validate the usability, clarity, and effectiveness of the system from the user's perspective. It highlights how users interact with various screens, receive feedback during critical moments, and are guided through emergency situations with minimal effort. By focusing on visible outcomes and interaction flow, this chapter confirms that the system is intuitive, responsive, and suitable for real-world emergency deployment.

7.1 Login and Signup Interface

The login and signup interface represents the entry point to the ResQNow application and serves as the first interaction between the user and the system. It allows users to securely authenticate themselves before accessing any emergency-related services, ensuring controlled and personalized usage of the application. Users can either log in using previously registered credentials or create a new account by providing basic details such as full name, email address, and password.

Figure **??** illustrates the login and signup screen of the ResQNow application. The interface is designed with a clean, minimal, and distraction-free layout to ensure ease of access even under stressful emergency conditions. Clear input fields, large action buttons, and intuitive navigation enhance usability and reduce user effort. Upon successful authentication, the user is seamlessly redirected to the main dashboard, confirming system readiness and enabling immediate access to emergency response features.

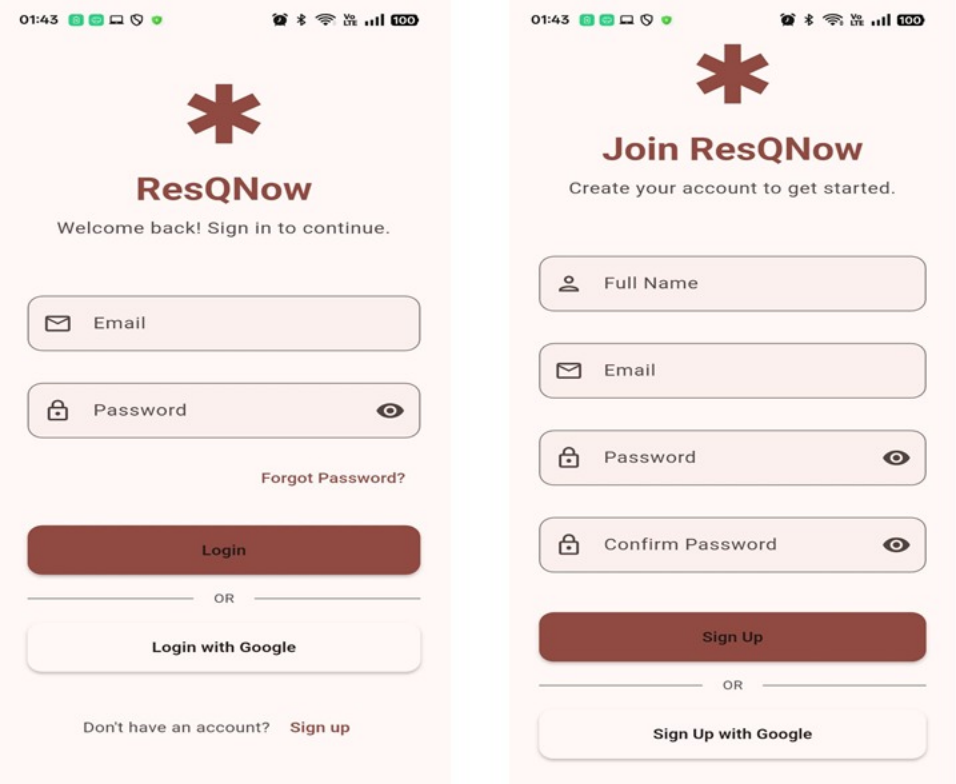

Figure 7.1: Login and signup interface of the ResQNow application

7.2 User Dashboard and Emergency Contact Management

After successful authentication, the user is presented with the ResQNow dashboard, which serves as the central control interface for all emergency-related actions. The dashboard provides quick access to core features such as AI assistance, BLE connectivity, AR guidance, and SOS triggering. It also displays recent SOS alerts along with their priority levels for improved situational awareness during critical emergency situations.

Figure **??** shows the dashboard interface of the ResQNow application. An important functionality available on this screen is the ability to add and manage **emergency contacts**. These contacts are automatically notified whenever an SOS is generated, ensuring that trusted individuals such as family members or close friends are immediately informed during emergencies and can respond without unnecessary

delay.

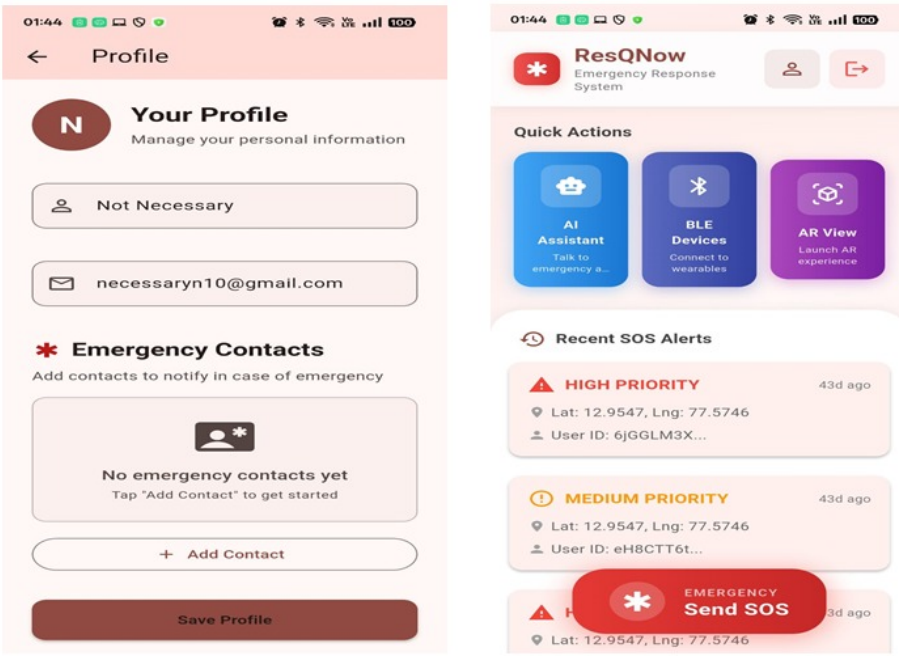

Figure 7.2: ResQNow dashboard showing quick actions, recent alerts, and emergency contact management

7.3 AI Chatbot Interaction and Automatic SOS Generation

One of the most significant user-facing features of ResQNow is the AI-powered emergency chatbot. The chatbot initiates a supportive and calming conversation with the user to understand the emergency context. It asks relevant questions, provides reassurance, and continuously analyzes user responses to assess risk.

Figure **??** illustrates the AI chatbot interaction along with the corresponding SOS alert details generated by the system. Based on conversational analysis, the AI automatically identifies the type and severity of the emergency. In high-risk situations, such as suspected cardiac events, the system automatically triggers an SOS without requiring manual confirmation. The alert is visible to multiple responders, and once one responder accepts the alert, others are notified that help is already in progress. The interface also provides a **"View Location on Map"**

option, which opens Google Maps with the live location of the affected user for accurate navigation.

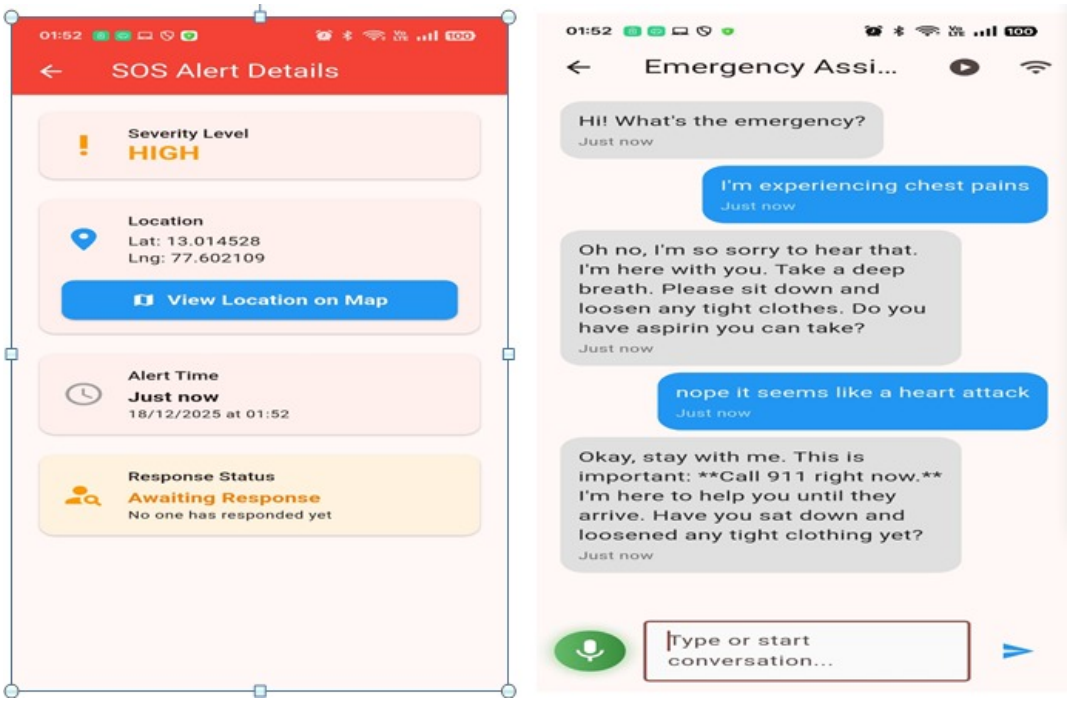

Figure 7.3: AI chatbot interaction and the corresponding SOS alert details generated by the system

7.4 Augmented Reality CPR Assistance Output

When immediate first-aid intervention is required, ResQNow activates real-time AR-based CPR guidance to assist the user during cardiac emergencies. From the user's perspective, visual markers, directional cues, and instructional overlays are superimposed directly onto the live camera feed, guiding correct hand placement, compression depth, and compression rhythm in real time under stressful emergency conditions.

Figure **??** shows the AR-based CPR guidance interface. The interface provides clear step-by-step instructions and visual feedback that help users maintain proper technique and consistency throughout the procedure. By translating medical instructions into intuitive visual cues, the system minimizes cognitive load and enables even untrained bystanders to confidently perform CPR. This reduces

hesitation, improves procedural accuracy, and increases the likelihood of effective intervention during critical, time-sensitive emergency situations with enhanced user confidence and situational awareness.

Figure 7.4: Augmented reality CPR guidance with visual hand-placement indicators

7.5 Augmented Reality AED Assistance Output

In addition to CPR guidance, ResQNow provides AR-based assistance for Automated External Defibrillator (AED) usage. The interface visually guides users through device activation, pad placement, and safety precautions in a step-by-step manner, ensuring clarity and confidence even for users with no prior medical training.

Figure **??** illustrates the AR-based AED guidance interface. The visual overlays significantly reduce hesitation and ensure correct AED usage during time-critical

cardiac emergencies by presenting clear instructions, safety warnings, and procedural sequencing, thereby improving the chances of survival before professional medical help arrives.

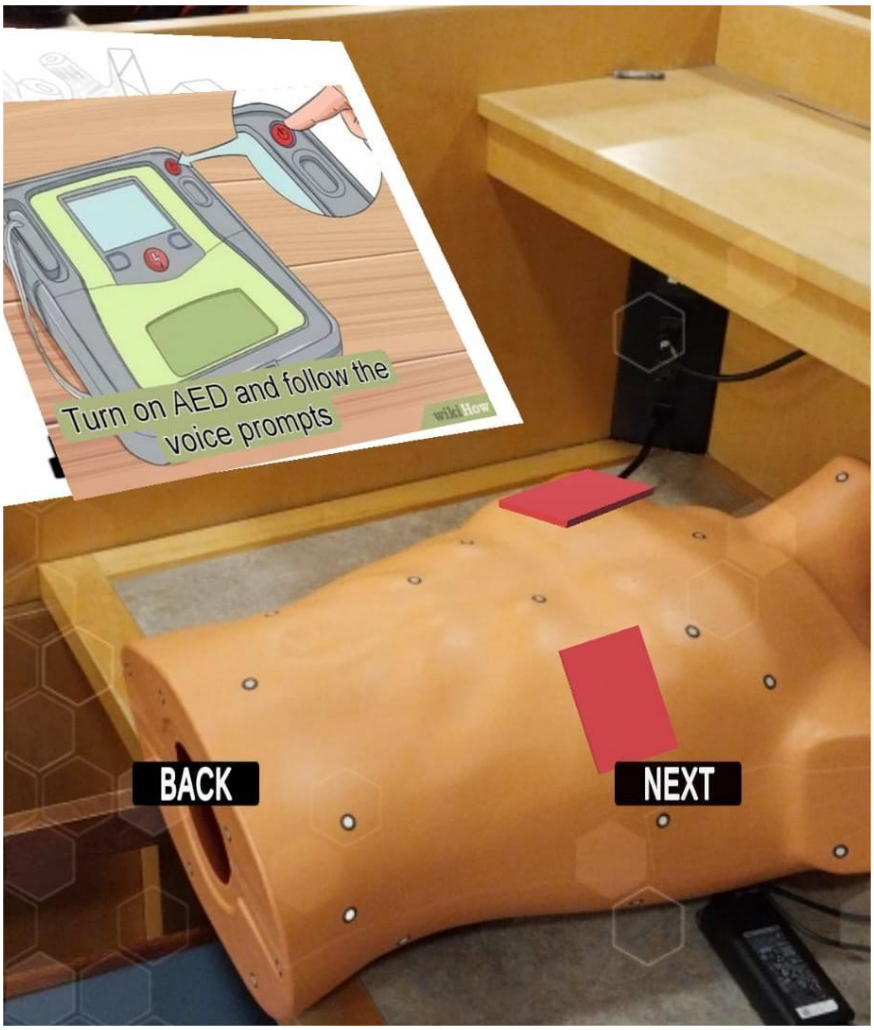

Figure 7.5: Augmented reality AED guidance displaying device operation and pad placement

7.6 Summary

This chapter presented the application-level results of the ResQNow emergency response system through its user interface. The results demonstrate secure authentication, intuitive dashboard navigation, effective emergency contact integration, AI-driven conversational emergency detection with automatic SOS generation, live location sharing for responders, and immersive AR-based first-aid

assistance for CPR and AED usage. By focusing exclusively on user-visible behavior and interaction flow, this chapter validates the system's usability, clarity, and readiness for real-world emergency deployment.

Chapter 8

Conclusion and Future Enhancements

This chapter summarizes the project outcomes and evaluates its effectiveness as an intelligent emergency response system. It highlights major contributions and discusses future enhancements to extend scalability and real-world applicability.

8.1 Conclusion

The **ResQNow** project integrates **AI**, **AR**, and **mobile communication technologies** to improve emergency response effectiveness. It enables rapid SOS activation, automated severity classification, GPS tracking, and AR-guided first aid, allowing untrained bystanders to assist confidently. Testing confirms low-latency alertsúSOS delivery, reliable BLE-based offline communication, and a secure, scalable Flutter–Firebase–FastAPI architecture suitable for real-world deployment.

8.2 Future Scope

The following enhancements can be considered to further improve the system:

- Deployment of optimized on-device AI models for fully offline emergency detection and classification
- Expansion of multi-hop BLE mesh networking with responder verification and reward mechanisms
- Multilingual and voice-driven AI assistant for hands-free emergency interaction and guidance
- Direct integration with hospitals, ambulance dispatch systems, wearable devices, and physiological sensors
- Advanced 3D AR-based first-aid guidance combined with predictive analytics and emergency risk mapping

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