AI-Driven Detection and Mitigation of Urban Heat Island Effects Using Image Analysis and IoT

R25-002

Project Proposal Report

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B.Sc. (Hons) Degree in Information Technology Specialized in Software Engineering

Department of Computer Science and Software Engineering
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Declaration

I hereby declare that the work contained in this proposal is entirely my own and has not been submitted, in whole or in part, for any degree or diploma at any other university or institution of higher education without proper acknowledgment. I confirm that all sources used have been appropriately cited and that this proposal is free from any form of plagiarism to the best of my knowledge and belief.

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The supervisor/s should certify the proposal report with the following declaration.

The above candidate is carrying out research for the undergraduate Dissertation under supervision of the undersigned.

23/01/2025

Signature of the supervisor
(Mr.Vishan Jayasinhearachchi)

Date

KR

23/01/2025

Signature of the co-supervisor
(Ms. Kaushalya Rajapakse)

Date

Abstract

Urban Heat Island (UHI) effects, characterized by elevated temperatures in urban environments compared to surrounding rural areas, present significant challenges in terms of public health, energy consumption, and environmental sustainability. Traditional methods for detecting and mitigating UHI effects often require expert consultations, which can be costly and inaccessible to many communities, limiting their ability to effectively address the issue. This research aims to democratize UHI detection and mitigation by developing an accessible, scalable system that integrates advanced technologies, such as Vision-Language Models (VLMs) and Large Language Models (LLMs), to analyze urban heat data and provide actionable recommendations.

A key component of this system involves the formalization and standardization of data, combining outputs from image segmentation and IoT-driven temperature mapping into a unified, structured format. Using image segmentation techniques, the system identifies specific urban features such as buildings, pavements, and other materials, and associates them with corresponding temperature readings collected by IoT devices. This data is then translated into a standardized format that includes information on material types, surface areas, and temperature values, allowing for seamless integration with AI-driven analysis tools.

By employing prompt engineering techniques, the system can fine-tune Vision-Language Models and Large Language Models, enabling them to interpret the standardized data and generate predictive insights. These insights can include recommendations for material replacements, building modifications, and other strategies to reduce heat absorption and mitigate UHI effects. The AI-driven approach enhances the precision of these recommendations, ensuring they are tailored to the specific characteristics of each urban area.

This framework is designed to be scalable, enabling the analysis of large datasets and the incorporation of new data sources as they become available. The standardized format ensures that the system can easily adapt to different regions, urban layouts, and heat-related challenges, while also making it easier for urban planners, policymakers, and communities to access expert-level insights without the high costs typically associated with traditional consulting services.

Ultimately, this research contributes to improved urban sustainability, increased climate resilience, and more effective environmental monitoring. By bridging the gap between visual and environmental data through the integration of image analysis and IoT technology, the framework offers a powerful tool for addressing UHI effects. This approach empowers decision-makers to implement evidence-based strategies that not only reduce the impact of UHI but also promote a more sustainable, resilient, and climate-adaptive urban environment for the future.

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List of abbreviations

AI	Artificial Intelligence
IoT	Internet of Things
UHI	Heat Island
VLM	Vision-Language Model

Introduction

Urban Heat Island (UHI) effects pose significant challenges to urban sustainability, necessitating innovative approaches for detection and mitigation. A critical aspect of addressing UHI lies in the standardization and integration of heterogeneous data sources, such as image segmentation outputs from satellite imagery and temperature readings from IoT sensors. These disparate data streams must be harmonized into a unified framework to enable effective AI-driven analysis. By formalizing data into standardized formats, such as JSON , compatibility with advanced AI models, including Vision-Language Models (VLMs) can be achieved, facilitating actionable insights for UHI mitigation [1].

One of the primary challenges in UHI detection is the accurate processing and interpretation of multimodal data, which combines visual data (thermal imagery) with environmental data (IoT sensor readings). Traditional data analysis methods often fail to integrate these diverse inputs effectively, leading to inefficiencies and inaccuracies in deriving actionable insights. Recent advancements in machine learning and natural language processing have enabled the standardization of such data, allowing seamless integration with predictive modeling tools [2]. For instance, prompt engineering techniques can fine-tune AI models to generate precise, context-specific recommendations for mitigating UHI effects, such as optimizing building materials or urban green spaces [3].

Scalability is another critical factor for the widespread adoption of UHI detection systems. As urban environments expand and new data sources emerge, the framework must accommodate larger datasets and evolving technologies. Standardized data formats, such as JSON, enable easy updates and extensions without requiring significant code changes, ensuring long-term adaptability [4]. This scalability also supports real-time decision-making, empowering urban planners and policymakers with up-to-date insights to inform climate resilience strategies and sustainable urban development practices [5].

The integration of AI-driven analysis into standardized data formats enhances the system's predictive capabilities. By processing vast amounts of environmental data, AI models can uncover hidden patterns and correlations that traditional methods might overlook, providing deeper insights into the drivers of UHI effects. Predictive modeling can simulate future temperature trends and evaluate the potential impacts of various mitigation strategies, guiding decision-making processes [6]. Ultimately, this research aims to democratize expert-level analysis, making UHI detection and mitigation accessible to a broader audience, including policymakers, urban planners, and communities, thereby fostering more sustainable and climate-resilient urban environments.

Background & Literature Survey

The integration of diverse data sources, such as temperature readings, geospatial information, and environmental sensor data, is critical for advancing Urban Heat Island (UHI) detection and mitigation. A key challenge in this integration is the standardization of data into a formalized, structured format, enabling its efficient use with advanced AI models like Vision-Language Models (VLMs) and Large Language Models (LLMs). This process ensures that data is scalable, flexible, and capable of accommodating future updates without requiring significant code changes.

In recent years, significant progress has been made in data standardization, particularly in the context of smart cities and environmental monitoring. For instance, Xie et al. (2017) proposed a data standardization framework for smart cities, emphasizing the need to structure raw data from various urban sensors into a unified format. This approach facilitates easier data integration and more accurate analysis, which is essential for UHI studies where harmonizing diverse sensor types is critical for effective environmental monitoring [7].

The role of prompt engineering, the process of designing inputs to guide AI models in generating desired output has also emerged as a pivotal area of research. Liu et al. (2020) developed a JSON-based schema for sensor data integration in environmental systems, enabling seamless interaction with AI models. Their work highlights how structured data can be efficiently processed, with prompt engineering playing a crucial role in defining how data is presented to LLMs and VLMs. This ensures that models interpret and utilize the data effectively to generate meaningful insights [8].

Further advancements in structured data formatting for machine learning tasks were explored by Zhang et al. (2021). They demonstrated how standardized data formats, such as JSON, streamline the prompt engineering process, ensuring consistent and reliable inputs for AI predictions. This approach is particularly important for integrating temperature readings, geospatial data, and other sensor data into models capable of predicting and mitigating UHI impacts [9].

The importance of scalable and flexible data structures for real-time urban monitoring was emphasized by Smith and Zhao (2019). Their study found that using adaptable formats like JSON or XML enables the integration of diverse sensor data from various environmental monitoring systems. This adaptability is crucial for UHI studies, where real-time, dynamic data is essential for generating accurate and timely predictions [10].

By focusing on standardized data formats and the critical role of prompt engineering, this research ensures that diverse environmental data can be effectively utilized by AI models. This leads to improved UHI detection, prediction, and mitigation strategies, ultimately contributing to more sustainable urban environments.

Research Gap

Urban Heat Island (UHI) detection and mitigation are critical for addressing climate change and improving urban living conditions. However, despite the growing body of research in this field, significant gaps remain in the integration of diverse data sources and their effective utilization for AI-driven models. One of the most pressing challenges is the lack of a standardized and scalable approach to representing and integrating heterogeneous data sources, such as temperature readings, geospatial coordinates, and thermal imagery, into a unified format that is compatible with AI models.

Current UHI detection systems are often hindered by rigid data structures that are not designed to integrate multiple data sources seamlessly. For instance, temperature sensors and thermal imaging systems typically provide data in different formats, making it difficult to combine this data into a cohesive system. Many systems rely on proprietary data formats or static schemas that cannot evolve as new data sources are added or as data collection methods improve. This lack of flexibility is particularly problematic for real-time applications, where new data must be integrated and processed quickly [11].

While some recent studies, such as Liu et al. (2021), have proposed standardized data formats like JSON for sensor data integration, these frameworks often focus on specific sensor types or domains, leaving gaps in the ability to unify data from a variety of environmental sources. For example, Liu's approach addresses integration for environmental sensors but fails to consider the dynamic nature of urban environments and the need for continuous updates as new data points are generated. Furthermore, current data schemas are often static, limiting their scalability as new sensor technologies and data types emerge. This lack of adaptability prevents effective data aggregation from diverse IoT-based systems, which could provide real-time insights into UHI patterns [12].

Another critical gap in current UHI detection systems is the lack of continuous data validation mechanisms. Real-time data collection, which is vital for accurate and actionable insights, often faces validation issues. While IoT-based systems can collect data in real-time, they lack the infrastructure to continuously verify the accuracy of the data being fed into AI models. For example, discrepancies in temperature readings from different sensors or misalignments between thermal images and geographical coordinates can result in inaccurate predictions about UHI effects. Real-time data validation ensures that the system can continuously monitor data quality, detect anomalies, and adjust predictions accordingly. However, existing systems generally rely on batch data processing or static models that do not have the capability to validate data as it is being collected.

In the context of AI-driven models, prompt engineering plays a pivotal role in ensuring that machine learning models interpret and process input data accurately and effectively. For instance, when integrating visual data (such as thermal imagery) with environmental data (like temperature readings), the prompt used to process this data needs to be carefully engineered to direct the model's attention to the relevant features of the data. However, existing UHI detection systems often overlook the importance of prompt engineering, relying on generic prompts or model inputs that fail to leverage the full potential of AI models.

As UHI detection and mitigation require large-scale implementations, the scalability and adaptability of data structures and AI models are essential. Existing systems typically struggle with scaling due to the rigid nature of their data models and the lack of standardization across different environmental data types. Moreover, as new data sources emerge, such as more advanced thermal imaging techniques or more accurate IoT sensors, existing systems must be able to adapt without requiring significant changes to their underlying data structures or AI models. A scalable system should be able to accommodate new types of sensors or imaging techniques without requiring a complete overhaul of the data integration process. This calls for a standardized approach to data representation that can easily evolve to incorporate emerging technologies.

TABLE 1 : COMPARISON BETWEEN EXISTING SYSTEMS

Feature	Research A [5]	Research B [6]	Research C [7]	Proposed Solution
Tailored Recommendations	X	X	X	✓
Prompt Engineering	X	X	✓	✓
Standardized Data Format	X	X	X	✓
Real-Time Data Integration	X	✓	X	✓

Research Problem

The central research problem identified in this study is the lack of a cohesive framework for generating actionable, localized recommendations for mitigating Urban Heat Island (UHI) effects. Existing UHI mitigation approaches are limited by their reliance on static data, lack of tailored strategies, and underutilization of advanced AI models. This research aims to address the following specific issues:

1. Lack of Context-Specific Recommendations
    - Traditional UHI mitigation methods, such as using reflective materials or increasing vegetation, provide generalized solutions that fail to account for the unique thermal and material characteristics of specific urban environments. These strategies often overlook localized heat distribution patterns, reducing their effectiveness.
2. Absence of Tailored Outputs from AI Models
    - While advanced AI models like Vision-Language Models (VLMs) have demonstrated capabilities in analyzing multi-modal datasets, they are not being effectively utilized to generate precise, actionable recommendations for UHI mitigation. Current approaches often produce generic outputs, lacking the specificity needed for real-world applications.
3. Lack of Prompt Engineering for Targeted Insights
    - Most existing AI systems are not designed to leverage prompt engineering, which is essential for guiding VLMs to interpret data effectively and generate meaningful insights. For example, without well-structured prompts, AI models cannot:
        - ✓ Identify materials that contribute most to heat retention.
        - ✓ Correlate localized temperature data with specific materials or surfaces.
        - ✓ Propose quantified impacts of mitigation strategies, such as the predicted reduction in surface or ambient temperatures.
4. Inability to Quantify Impact
    - Existing systems rarely provide quantified assessments of proposed interventions. For instance, while recommendations like adding rooftop gardens or replacing asphalt with reflective coatings are common, they often lack precise data on how much these changes will reduce temperatures. This limits the ability of urban planners to evaluate and prioritize interventions effectively.
5. Scalability and Adaptability Challenges
    - Traditional approaches struggle to scale across diverse urban contexts or adapt to rapidly changing environmental conditions. Without a flexible framework, urban planners are left with static solutions that fail to address the dynamic nature of UHI effects.

Proposed Research Focus

To address these challenges, this research proposes a framework that integrates Vision-Language Models (VLMs) with prompt engineering to generate actionable, localized, and quantified recommendations for UHI mitigation. By synthesizing segmented imagery and contextual prompts, the system will provide:

- Material-specific insights to reduce heat absorption.
- Localized greening strategies for optimal cooling effects.
- Quantified impact assessments to guide urban planners in implementing the most effective interventions.

This approach ensures that UHI mitigation strategies are not only practical and effective but also scalable and adaptable to various urban settings.

Objectives

Main Objective

The main objective of this research is to develop a standardized and scalable solution for integrating data outputs from multiple sources (such as semantic segmentation and IoT-based temperature mapping) into a unified format that enables effective and efficient interaction with Vision-Language Models (VLMs) and Large Language Models (LLMs). The proposed system focuses on creating a formalized data representation that allows easy integration of segmented image data, temperature maps, and other relevant information for AI-driven analysis. The system aims to support dynamic and real-time data analysis by ensuring that new fields can be seamlessly added with minimal code changes. By enhancing the prompt engineering process, this research strives to optimize the integration of complex urban data into AI models for better prediction, mitigation, and sustainable urban planning.

Specific Objectives

- **Standardized Data Representation** : Develop a formalized and standardized data format (such as JSON) to combine outputs from image segmentation, temperature data, and other relevant sources, enabling easy integration with VLMs and LLMs.
- **Data Scalability and Flexibility** : Ensure the data format is scalable, allowing new data fields to be added with minimal changes to the existing codebase and accommodating growing datasets.
- **Real-Time Data Integration** : Enable real-time integration of temperature data and segmented imagery to allow for up-to-date analysis and decision-making in UHI mitigation efforts.
- **Optimization of Prompt Engineering** : Develop a method for fine-tuning prompts to extract specific information from standardized data, improving the quality and relevance of responses generated by AI models.
- **Enhanced Model Interoperability** : Facilitate the seamless integration of diverse urban data sources into Vision-Language Models (VLMs) for structured input/output, enhancing the overall effectiveness of predictive modeling.
- **Support for Urban Sustainability** : Provide a robust foundation for AI-driven analysis that supports sustainable urban growth and climate resilience by offering valuable insights into urban heat management.

Methodology

System Overview

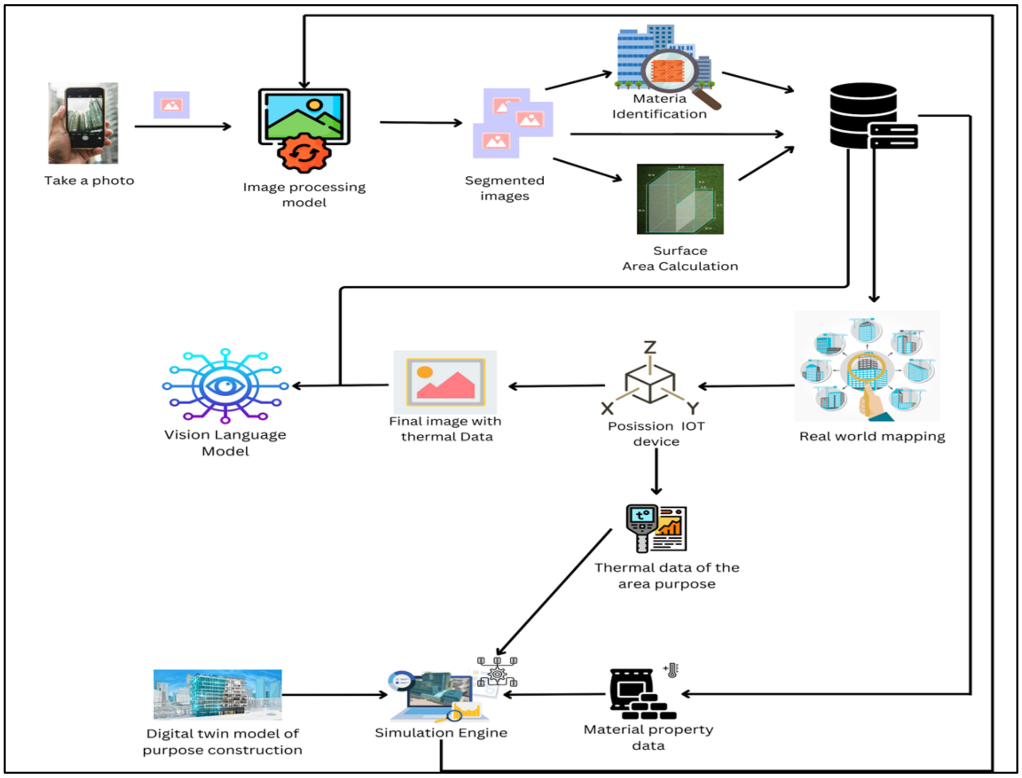

FIGURE 1: SYSTEM OVERVIEW DIAGRAM

The system diagram for the research topic, AI-driven detection and mitigation of urban heat island (UHI) effects through image analysis and IoT integration, will illustrate the complete workflow of the project. The diagram will depict how images of urban environments are processed to identify and segment key elements like buildings, vegetation, and surfaces, followed by material prediction (e.g., concrete, glass) and surface area calculation. Simultaneously, IoT devices will collect real-time temperature data from various urban locations. These components will integrate to create an annotated dataset combining visual and environmental data, standardized into a JSON format. This JSON will serve as input for Vision-Language Models (VLMs), incorporating text prompts, original images, segmentation maps, and temperature data. The VLM will analyze this integrated input to generate contextualized insights, aiding in identifying UHI patterns and suggesting mitigation strategies such as green cover expansion or material modifications for sustainable urban planning.

My Component

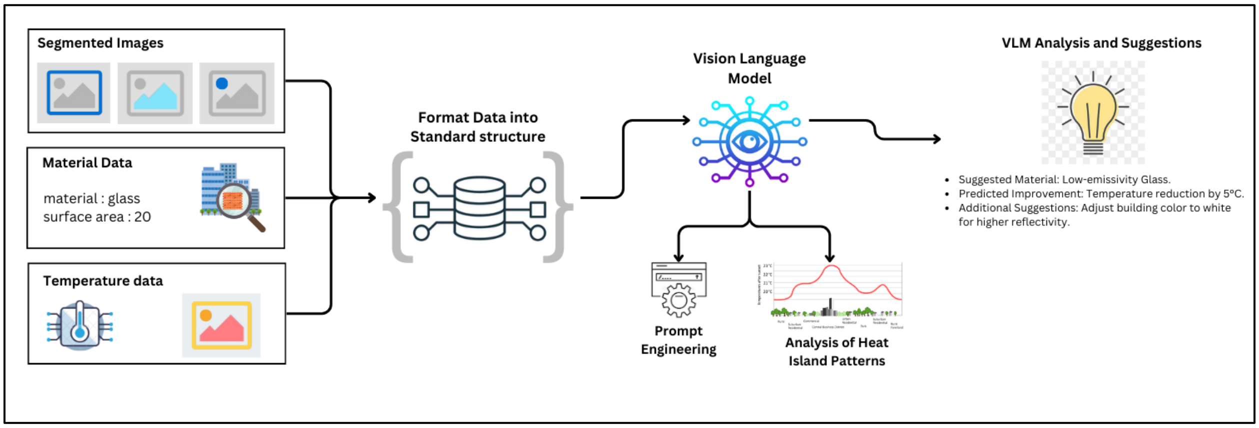

FIGURE 2 : HIGH LEVEL ARCHITECTURE DIAGRAM

As depicted in the figure, the proposed system's third component is designed to facilitate the standardized representation of data outputs, ensuring effective integration with Vision-Language Models (VLMs) or Large Language Models (LLMs) for structured input/output. The first step in the process is to collect and format the data generated by segmented images and temperature data into a standardized format. This ensures the data is scalable, and new fields can be added with minimal code changes, allowing easy adaptation as new information is generated.

The next step involves prompt engineering, where the standardized data is used to fine-tune prompts for VLMs. The goal is to design effective prompts that can extract specific information from the data, such as identifying thermal hotspots or mapping temperature trends. The data is then passed through the model, which processes it in accordance with the prompts to generate actionable insights.

Prompt engineering plays a crucial role in ensuring that the input data is interpreted in a way that aligns with the desired outputs, allowing the models to provide accurate, relevant predictions. By fine-tuning the prompts, the system can optimize the information it receives, ensuring the results are as accurate and actionable as possible.

The final step is to integrate the processed outputs into a usable format for decision-making. The output from the models will be in a standardized format, ready for analysis by urban planners and policymakers. This allows for real-time, informed decision-making regarding the mitigation of Urban Heat Island (UHI) effects, ensuring the outputs from the models are both actionable and aligned with urban planning requirements.

TABLE 2 : TECHNOLOGIES, TECHNIQUES, ARCHITECTURES, AND ALGORITHMS USED.

Technologies	Standardized Data Formats (e.g., JSON, XML), VLM Integration Platforms (e.g., OpenAI, GPT models), Cloud storage (Azure/AWS)
Techniques	Data normalization, Prompt engineering for model integration, Standardized data representation
Algorithms	Data parsing algorithms, Prompt tuning for model optimization, Integration algorithms for VLM/LLM outputs

Software Solutions

Development Process

To implement my component of this research, standardize the outputs from segmented images and temperature data into a formalized format that can seamlessly integrate with Vision-Language Models (VLMs) utilize advanced techniques such as prompt engineering to ensure that the model accurately interprets the input data and provides actionable insights for Urban Heat Island (UHI) mitigation.

The project will involve three main steps:

1. Data Collection & Formatting:
   - The temperature data (collected from IoT sensors) and segmented images will be processed and formatted into a standardized format such as JSON. This will involve ensuring that the data is structured in a way that it can easily integrate with VLMs.
2. Prompt Engineering:
   - The standardized data will be used to craft specific prompts to fine-tune the VLM, guiding the model to extract relevant and actionable insights such as identifying UHI hotspots and predicting temperature trends in urban areas.
3. Integration & Validation:
   - After the prompts are fine-tuned, the results will be validated to ensure that the outputs align with urban planning goals and real-world requirements for UHI mitigation. The validated output will be presented in a usable format, enabling decision-makers to take actionable steps.

Tasks and Sub-Tasks

1. Task 1: Data Formatting and Standardization
   - Sub-task 1.1: Collect data from segmented images and temperature readings.
   - Sub-task 1.2: Format the data into a standardized format (e.g., JSON).
   - Sub-task 1.3: Ensure that the data can scale with minimal changes.

2. Task 2: Prompt Engineering
   - Sub-task 2.1: Design prompts to extract specific information from the standardized data.
   - Sub-task 2.2: Fine-tune the prompts for VLMs.
   - Sub-task 2.3: Test the prompts with sample data to ensure optimal performance.

3. Task 3: Integration and Validation
   - Sub-task 3.1: Pass the standardized data through the VLM and generate insights.
   - Sub-task 3.2: Validate the outputs to ensure they align with urban planning needs.
   - Sub-task 3.3: Format the outputs for decision-makers to take actionable steps.

Data Collection

The project requires the following data:

- Temperature Data: Collected from IoT temperature sensors deployed in urban areas.
- Segmented Images: Derived from semantic segmentation of urban surfaces.

The data will be collected via automated sensors and cameras in urban environments, which will feed data into cloud storage platforms for processing. The data will be formatted into JSON for integration with the model.

Commercialization

Target Audience

- Urban Planners and City Officials
- Environmental Researchers
- Data Scientists and AI Researchers
- Innovators and Tech Startups

Market Space

- AI and Machine Learning Technologies
- Urban Development and Smart Cities
- Environmental Monitoring and Climate Tech
- Data Integration and IoT Solutions

Project Requirements

Functional Requirements

- Data Standardization: The system must ensure that temperature data and image segmentation results are combined into a standardized format for seamless integration with VLMs.
- Automated Data Integration: The system must automate the merging of temperature data with segmented images to create a unified dataset.
- Data Validation: The system must validate the integrated data to ensure consistency and accuracy.
- Output Format: The system should output the standardized data in a format suitable for VLM processing, ensuring easy scalability and adaptability.

Non – functional Requirements

- Efficiency: The system should process and standardize large volumes of data quickly to ensure timely analysis.
- Scalability: The system should be able to scale as the amount of data from IoT sensors and image segmentation increases.
- Accuracy: The system must maintain high accuracy in integrating temperature data with image segmentation results.
- Interoperability: The standardized data must be compatible with multiple VLMs for integration and analysis.

User Requirements

- Data Access: Users must be able to easily access and view the standardized data for analysis and decision-making.
- Customization: Users should be able to customize how the data is represented and filtered based on specific needs (e.g., by temperature, area).
- Alerts: Users should receive notifications when data anomalies or issues are detected in the standardized dataset.

System Requirements

- Data Storage: Cloud storage services (e.g., AWS, Azure) for storing collected data.
- Processing Tools: Software tools for processing, standardizing, and integrating temperature data and image segmentation results.
- Database: A database (e.g., PostgreSQL, SQL) for storing and retrieving the standardized data.
- Data Format Tools: Tools to ensure the data is represented in a format compatible with VLM integration.

Use case Scenario

User Case ID	UC-001	
Use Case Name	Standardized Data Integration and VLM Optimization	
Priority	High	
Preconditions	• Input data (image, temperature, material information) is available. • Data must be structured in a standardized format (JSON, image, text). • The system must have access to a Vision-Language Model (VLM).	
Post-conditions	• The VLM processes the input data and generates structured insights. • The output follows a standardized format for scalability. • The system refines the output using prompt engineering techniques.	
Primary actor	System (VLM Integration Module)	
Trigger	User submits input data for analysis	
Main scenario	**Steps ID**	**Action**
	1	User uploads an image and corresponding metadata (temperature, material, area, etc.).
	2	The system validates the format and standardizes the input (image, JSON, text).
	3	The standardized data is sent to the Vision-Language Model (VLM).
	4	The model generates an initial response based on the input.
	5	The system applies prompt engineering techniques to refine the query.
	6	The VLM processes the refined prompt and generates an optimized structured output.
	7	The output is stored in a database and displayed to the user.
	8	The user can review, modify, or export the results.
Extensions	**Steps ID**	**Branching Action**
	2a	If the uploaded data format is incorrect, the system prompts the user to re-upload.

	4a	If the initial response lacks accuracy, prompt tuning is applied iteratively.
	7a	If the generated output does not meet the standard format, the system retries with a modified prompt.
	8a	If the user requires additional refinement, manual adjustments or retraining may be initiated.

TABLE 3 : USE CASE SCENARIO

Test Cases

Test case ID	Test_01			
Test title	JSON Data Standardization Test			
Test priority (High/Medium/Low)	High			
Module name	Standardized Data Integration			
Description	This test ensures that the system correctly formats and stores image segmentation, material, surface area, and temperature data into a standardized JSON format for VLM processing.			
Pre-conditions	The system has successfully processed an image, predicted materials, calculated surface area, and received IoT temperature data.			
Test ID	Test Steps	Expected Output	Actual Output	Result (Pass/Fail)
Test_01	1. System collects processed data from segmentation, material prediction, surface area calculation, and IoT sensors. 2. System structures the data into a standardized JSON format.	JSON output follows the predefined schema with all required fields (image, segmentation, material, surface area, temperature).	JSON output is correctly formatted.	Pass

TABLE 4 : TEST CASE 1

Test case ID	Test_02			
Test title	VLM Input Processing Test			
Test priority (High/Medium/Low)	High			
Module name	VLM Optimization			
Description	This test ensures that the Vision-Language Model (VLM) correctly processes the standardized input (text, image) and does not produce errors.			
Pre-conditions	The JSON data is correctly formatted and passed to the VLM.			
Test ID	Test Steps	Expected Output	Actual Output	Result (Pass/Fail)
Test_02	1. System sends JSON input (text, image) to the VLM. 2. VLM processes the input without errors.	VLM successfully ingests and processes the input.	VLM correctly processes the input.	Pass

TABLE 5: TEST CASE 2

Test case ID	Test_03			
Test title	VLM Output Accuracy Test			
Test priority (High/Medium/Low)	High			
Module name	VLM Optimization			
Description	This test ensures that the VLM provides accurate contextualized analysis based on the given standardized input.			
Pre-conditions	The VLM has successfully processed the input data.			
Test ID	Test Steps	Expected Output	Actual Output	Result (Pass/Fail)
Test_02	1. System provides the JSON input to the VLM. 2. VLM generates an analysis report.	VLM provides a meaningful and accurate analysis (e.g., urban heat impact, material properties).	VLM output is accurate and relevant.	Pass

TABLE 6 : TEST CASE 3

Wireframes

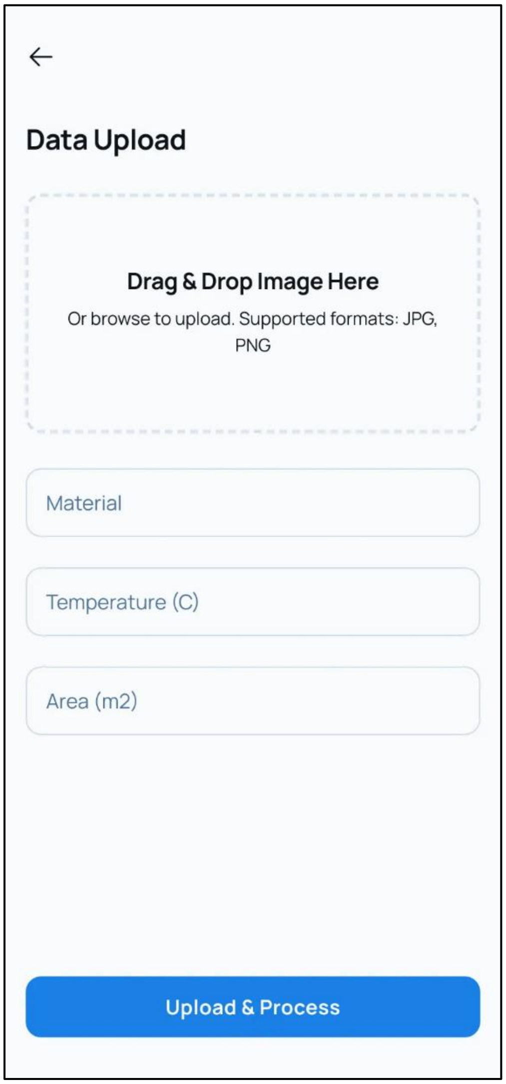

FIGURE 3 : WIREFRAME 1

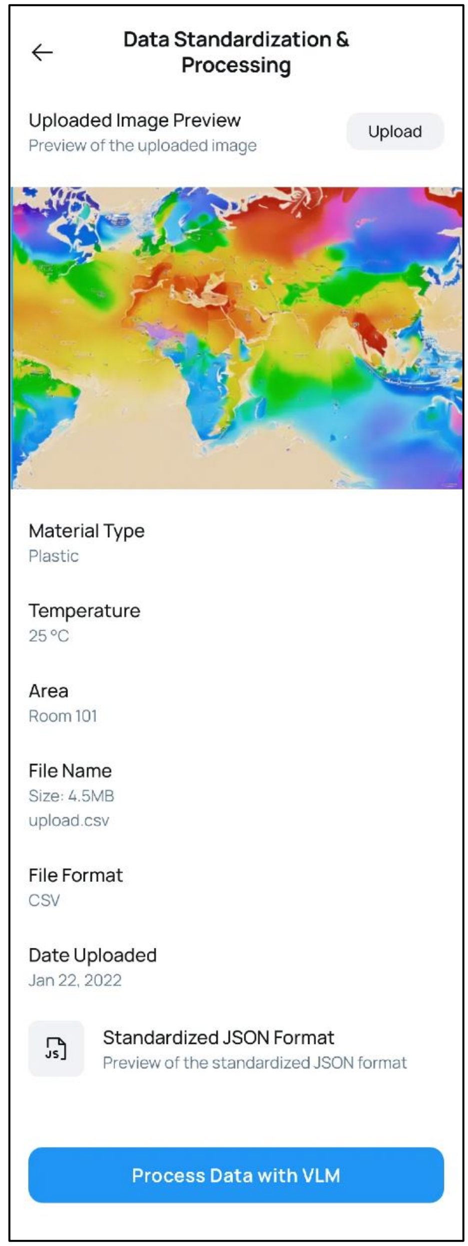

FIGURE 4 : WIREFRAME 2

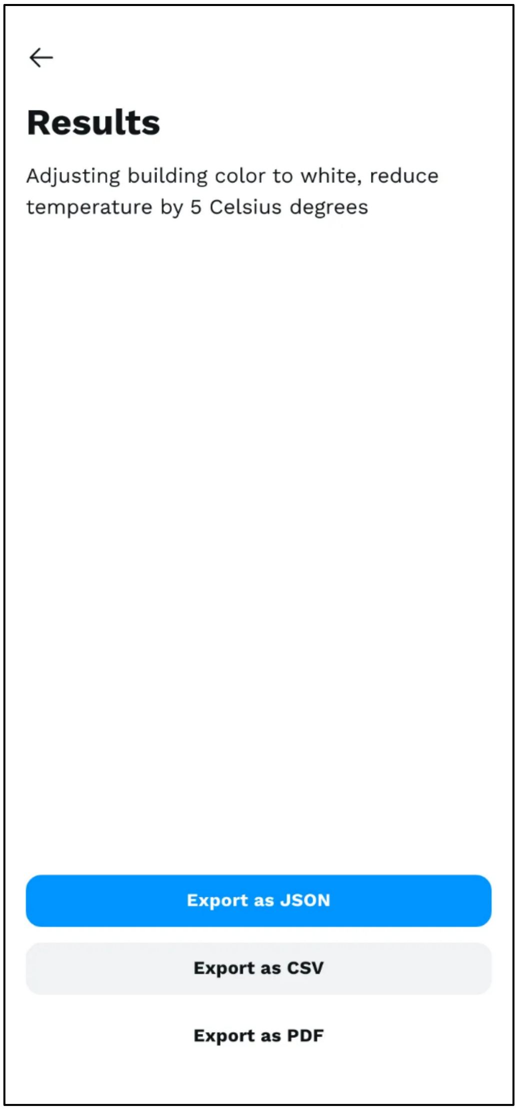

FIGURE 5 : WIREFRAME 3

Gantt chart

FIGURE 6 : GANTT CHART

Work Breakdown Structure

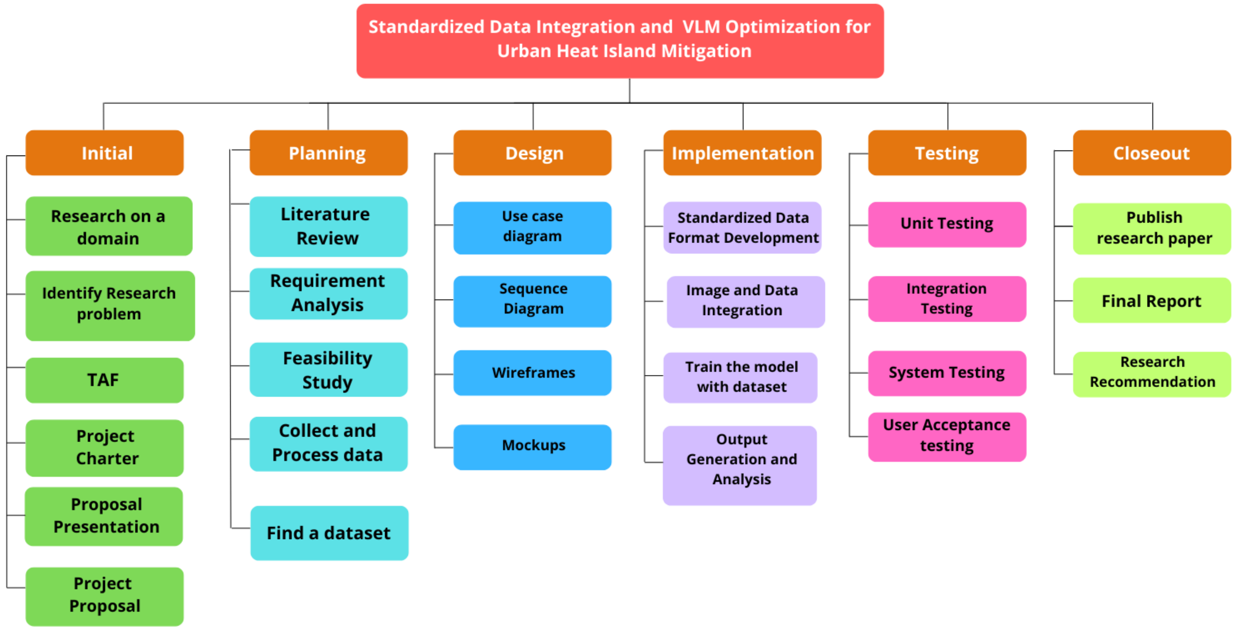

FIGURE 7 : WORK BREAKDOWN STRUCTURE

Budget

Requirements	Price (Rs.)
Cloud Computing Service	10000
Domain registration	4000
Hardware products	20000
Internet and Wi-Fi charges	6000
Total estimated cost	40000

TABLE 7 : BUDGET PLAN

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