DETECTION AND MITIGATION OF URBAN HEAT ISLAND EFFECT USING VISION-LANGUAGE MODELS

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DECLARATION

I declare that this is my own work, and this proposal does not incorporate without acknowledgement any material previously submitted for a degree or diploma in any other university or Institute of higher learning and to the best of our knowledge and belief it does not contain any material previously published or written by another person expect where the acknowledgment is made in the text.

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The above candidates are carrying out research for the undergraduate Dissertation under my supervision.

--- 29/08/2025

Signature of the Supervisor: Date:

ABSTRACT

Urban Heat Islands (UHIs) present significant challenges to sustainable urban development, leading to elevated local temperatures, increased energy demand, and adverse health outcomes. This study focuses on the integration of advanced machine learning and vision–language models (VLMs) to detect and mitigate UHI effects. The proposed component utilizes a two-stage approach: first, a logistic regression model trained on a Kaggle dataset of urban environmental factors predicts the presence of a UHI using structured metadata, including location type, material type, surface area, temperature, and humidity. If a UHI is detected, the system leverages Gemini (gemini-1.5-flash) as a VLM to analyze both the segmented urban imagery and associated metadata. Through carefully engineered prompts, Gemini generates low-cost and practical mitigation strategies, such as enhancing vegetation cover, applying reflective materials, or integrating water-based cooling features.

Furthermore, the component incorporates Explainable AI (XAI) techniques to justify both the detection and the recommended interventions, thereby improving transparency and decision-making for urban planners and policymakers. The results demonstrate that combining structured predictive modeling with Gemini's multimodal reasoning capabilities provides a scalable, intelligent framework for addressing UHIs. This hybrid approach enhances interpretability, ensures actionable outcomes, and contributes to climate-resilient urban planning.

Keywords

Urban Heat Island (UHI), Vision–Language Model (VLM), Gemini, Logistic Regression, Segmented Image Analysis, Environmental Metadata, Prompt Engineering, Explainable AI (XAI), Low-Cost Mitigation Strategies, Climate-Resilient Urban Planning.

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LIST OF ABBREVIATIONS

Abbreviation	Description
AI	Artificial Intelligence
API	Application Programming Interface
IoT	Internet of Things
ML	Machine Learning
UHI	Urban Heat Island
VLM	Vision–Language Model
XAI	Explainable Artificial Intelligence

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INTRODUCTION

1.1 Overview

Urban Heat Islands (UHIs) have emerged as a pressing concern in rapidly urbanizing regions, where built environments consisting of asphalt, concrete, and glass significantly amplify local temperatures compared to surrounding rural areas. Addressing this challenge requires not only accurate detection but also actionable and cost-effective mitigation strategies. This research component is designed to bridge the gap between traditional predictive modeling and modern multimodal artificial intelligence by integrating a machine learning classifier with a powerful Vision–Language Model (VLM).

The proposed framework first leverages structured environmental data such as temperature, humidity, material type, location type, and surface area to predict the likelihood of UHI formation using a logistic regression model trained on a Kaggle dataset. Once the system identifies a potential UHI, the decision-making process transitions into the Gemini (gemini-1.5-flash) VLM, which can analyze both segmented urban images and environmental metadata simultaneously. Through prompt engineering, Gemini generates low-cost, practical mitigation strategies tailored to the given urban context. These strategies may include increasing vegetation cover, implement reflective or porous materials, or introduce water-based cooling systems.

In addition to prediction and recommendation, this component also emphasizes Explainable AI (XAI) to ensure that both detection outcomes and suggested interventions are accompanied by clear reasoning. By combining structured ML predictions with Gemini's advanced multimodal reasoning, the system provides a scalable, transparent, and intelligent approach to UHI management, aimed at supporting urban planners and policymakers in building climate-resilient cities.

1.2 Background and Literature review

Technology has emerged as a critical enabler in addressing environmental and climate-related challenges, particularly the effect of Urban Heat Island (UHI). UHI refers to the elevated temperature of urban areas compared to surrounding rural regions, largely due to impervious materials such as asphalt, concrete, and glass that absorb and retain heat. Numerous studies have documented the negative consequences of UHIs, including increased cooling energy demand, higher greenhouse gas emissions, degraded air quality, and adverse health outcomes during heat waves [1], [2]. As cities continue to expand, scalable and intelligent solutions for UHI detection and mitigation have become an urgent priority for sustainable urban planning.

Early research on UHI relied heavily on remote sensing techniques and in-situ measurements. Satellite imagery from platforms such as Landsat, MODIS, and Sentinel has been widely used to estimate Land Surface Temperature (LST), vegetation indices, and impervious surface fractions [3]. Zhao et al. emphasized the role of vegetation in reducing UHI intensity while confirming impervious surfaces as dominant contributors to heat amplification [4]. More recent reviews have highlighted the advantages of remote sensing in terms of spatial coverage but also noted key limitations such as cloud dependence, coarse temporal resolution, and limited capacity for localized real-time predictions [5], [6]

To overcome these constraints, machine learning (ML) techniques have been adopted for UHI analysis. Random Forest (RF), Support Vector Machines (SVM), Gradient Boosting, and ensemble learning methods have shown strong predictive power in mapping UHI hotspots [7], [8]Mansouri et al. demonstrated that XGBoost outperformed traditional regression models, achieving high ROC-AUC scores (>0.90) for UHI prediction across U.S. cities [9]. Similarly, Kong et al. applied Support Vector Regression (SVR) to 216 global cities and identified wind speed and coastal proximity as key modifiers of UHI severity [10]. Other works integrated socio-economic and demographic data into ML frameworks, enhancing prediction accuracy but offering limited actionable guidance for planners [11].

Parallel to ML adoption, simulation-based approaches such as ENVI-met and InVEST have been employed to represent physical processes including shading, evapotranspiration, and surface albedo [12]. Bosch et al. demonstrated the potential of ENVI-met to simulate the spatial cooling benefits of urban greenery [13]. Despite their accuracy, these models are computationally intensive and less adaptable to dynamic urban conditions, reducing their scalability for real-time applications [14].

In recent years, Vision–Language Models (VLMs) have emerged as a novel paradigm for integrating multimodal inputs (images, structured data, and text) to support contextual reasoning. Unlike conventional ML models that produce purely statistical outputs, VLMs can generate human-readable, action-oriented recommendations. Bieri et al. introduced OpenCity3D, applying VLMs to infer demographic and structural characteristics from urban imagery [15]. Ma et al. demonstrated the application of Gemini in simulating pedestrian heat exposure and adaptive route planning, highlighting its promise for climate adaptation contexts [16]. These explorations show that VLMs hold potential to bridge the gap between prediction and decision support in urban environments.

The integration of Google's Gemini (gemini-1.5-flash) in this study represents a novel contribution to UHI research. Unlike previous works that primarily focused on detection, this hybrid pipeline combines a logistic regression classifier, trained on Kaggle-derived datasets, with Gemini's reasoning capabilities. Logistic regression provides a fast and interpretable UHI predictor using structured features (temperature, humidity, material type, and surface area). When UHI is detected, Gemini processes the segmented images and metadata to generate low-cost, context-sensitive mitigation strategies, such as rooftop greening, reflective pavements, and roadside vegetation.

Finally, the growing importance of Explainable AI (XAI) in environmental applications cannot be overlooked. Researchers have warned that while ML models achieve high accuracy, their "black-box" nature hinders adoption in policymaking [7], [9], [17]By integrating SHAP explainability for detection and rationale outputs from Gemini, this study ensures transparency. Decision-makers can thus understand not only what the system predicts or recommends, but also why.

In summary, the literature illustrates a clear trajectory: from remote sensing and physical simulation, toward ML-based prediction, and now into VLM-powered decision-support frameworks. This research situates itself in that progression, showing how Gemini VLM, combined with logistic regression and XAI, can provide a scalable, interpretable, and actionable framework for addressing Urban Heat Islands in modern cities.

1.3 Research Gap

1.3.1. Background and Theoretical Basis

In the context of contemporary climate research, Urban Heat Islands (UHIs) have been extensively studied using remote sensing, simulation-based modeling, and machine learning (ML) approaches. Remote sensing platforms such as Landsat, Sentinel, and MODIS have been widely deployed to measure land surface temperature (LST) and estimate UHI intensity at city and regional scales [1], [2]. These methods have proven effective in large-scale monitoring but suffer from notable constraints, including limited temporal resolution, dependency on atmospheric conditions, and reduced ability to capture micro-scale variations in heterogeneous urban landscapes. Simulation approaches, including tools like ENVI-met, offer valuable insights into the thermodynamic processes underlying UHI formation by modeling factors such as shading, evapotranspiration, and surface reflectivity [3]. However, these simulations are computationally expensive, require extensive calibration, and remain inaccessible for real-time operational use in fast-growing urban settings.

More recently, machine learning models have been applied to predict UHI intensity using diverse environmental and socio-demographic variables. Random Forest, Gradient Boosting, and Support Vector Regression (SVR) have demonstrated high predictive accuracy in identifying spatial heat patterns and quantifying the influence of urban morphology [4], [5]. Mansouri et al. [6] and Syeda et al. [7] showed that ML can integrate land cover, vegetation indices, and meteorological data to achieve reliable predictions of UHI severity. Yet, these models remain predominantly statistical in nature, offering detection and prediction, but falling short in action-oriented recommendations. Furthermore, the “black box” nature of advanced ensemble models reduces interpretability, limiting their utility for policymakers and urban planners who require transparent, explainable insights.

The theoretical basis for this study lies at the intersection of predictive modeling and Vision–Language Models (VLMs). Unlike classical ML, VLMs such as Gemini (gemini-1.5-flash) are designed to process multimodal data inputs, including imagery, structured metadata, and natural language prompts, and to generate context-aware outputs. Early experiments in applying VLMs to urban contexts (e.g., OpenCity3D [8]) highlight their ability to infer urban attributes from visual data, while Ma et al. [9] demonstrated Gemini’s adaptability in heat-sensitive pedestrian routing. This body of work aligns with constructivist AI theory, which emphasizes systems that not only analyze data but also produce adaptive, user-centered outputs that empower decision-making. In the context of UHI, this suggests a potential paradigm shift: from passive detection to intelligent recommendation systems that integrate prediction, reasoning, and explanation.

1.3.2. Review of Related Academic Work

Research A: "Machine Learning Prediction of UHI Severity" [6]

Mansouri et al. employed ensemble learning techniques (Random Forest, XGBoost) to predict UHI severity across Midwestern U.S. cities. The models achieved high accuracy and integrated SHAP analysis for partial interpretability. While effective for prediction, the framework offered no pathway for practical intervention, thus leaving a critical gap between analysis and actionable outcomes.

Research B: "Remote Sensing Approaches for UHI Assessment" [2]

Zhao et al. synthesized satellite-based approaches for monitoring UHIs, highlighting vegetation and impervious surfaces as dominant contributors. Although remote sensing provides essential data for UHI detection, its reliance on retrospective imagery limits its usefulness in real-time mitigation planning, particularly at micro-urban scales where interventions must be context specific.

Research C: "Simulation of Urban Cooling Effects with ENVI-met" [3]

Bruse and Fleer developed ENVI-met as a simulation tool for modeling surface–plant–air interactions. This approach has proven valuable for testing the cooling impacts of green infrastructure and reflective surfaces. However, the computational overhead and expertise required for simulation hinder its deployment in operational urban management.

Research D: "OpenCity3D: VLMs for Urban Analytics" [8]

Bieri et al. introduced OpenCity3D, showcasing VLMs' ability to analyze urban 3D reconstructions and infer socio-environmental attributes. While pioneering, the system focused on descriptive analytics rather than prescriptive strategies, and it did not integrate environmental metadata such as temperature or humidity—key factors in UHI assessment.

1.3.3. Synthesis of Literature and Identified Research Gap

The reviewed literature demonstrates substantial progress in UHI detection and prediction, spanning remote sensing, simulation, and ML-based approaches. However, a recurring limitation across these studies is the absence of systems that move beyond prediction to provide practical, low-cost, and context-specific mitigation recommendations. Traditional remote sensing and simulation approaches are either retrospective or computationally intensive, reducing their operational applicability. Meanwhile, ML models offer predictive power but lack explainability and fail to generate actionable interventions.

Although emerging work with Vision–Language Models shows promise in urban analytics, no comprehensive framework currently exists that integrates structured ML-based detection with VLM-based multimodal reasoning for UHI mitigation. Moreover, few studies address the need for Explainable AI (XAI) in this domain, despite its importance in ensuring transparency and stakeholder trust.

This study addresses these deficiencies by developing a hybrid framework that combines:

1. Logistic Regression trained on environmental datasets to provide transparent, interpretable UHI detection.
2. Gemini (gemini-1.5-flash) VLM to process segmented images and metadata, producing low-cost, context-specific mitigation strategies.
3. XAI integration to justify both detection outcomes and mitigation recommendations, ensuring actionable and trustworthy outputs.

By bridging the gap between detection and decision-making, this component introduces a novel paradigm for UHI management. It situates itself at the forefront of environmental AI research by demonstrating how multimodal reasoning can transform predictive analytics into intelligent, explainable, and actionable interventions for climate-resilient urban planning.

Application Reference	**Real-time Detection**	**Actionable Recommendations**	**Multimodal Reasoning (Image + Metadata)**	**Explainability (XAI)**	**Low-cost Mitigation Focus**
Research A – ML Prediction (Mansouri et al.)	✅	❌	❌	⚠️ (Partial with SHAP)	❌
Research B – Remote Sensing (Zhao et al.)	❌	❌	❌	❌	❌
Research C – Simulation (ENVI-met, Bosch et al.)	❌	✅	❌	❌	❌
Research D – VLM for Urban Analytics (OpenCity3D)	❌	❌	✅	❌	❌
Proposed System (Gemini + LR + XAI)	✅	✅	✅	✅	✅

Table 1: Comparison of Research Papers

1.4 Research Problem

This study addresses several critical challenges within the domain of Urban Heat Island (UHI) detection and mitigation, specifically focusing on the integration of machine learning models with Vision–Language Models (VLMs). Drawing from gaps identified in existing literature and technological practices, five principal research problems were examined. Each problem explored a distinct dimension of advancing UHI research through predictive analytics, multimodal reasoning, and actionable urban intervention strategies.

1. Limitations of Existing UHI Prediction Systems

Current UHI detection approaches—ranging from remote sensing to simulation-based modeling—were found to provide only partial insights into the problem. Remote sensing systems are heavily dependent on satellite imagery, often constrained by temporal resolution, atmospheric interference, and a lack of micro-scale precision. Simulation tools such as ENVI-met offer detailed physical modeling but are computationally expensive and impractical for real-time deployment. Machine learning models, while offering predictive power, are typically limited to numerical detection without the capacity to translate results into practical, low-cost mitigation strategies. This study identified these limitations and focused on addressing the lack of end-to-end frameworks capable of bridging prediction with actionable outcomes.

2. Lack of Action-Oriented Decision Support

Most existing systems for UHI research emphasize detection and characterization, but very few extend into the domain of decision support for urban planners. The absence of systems that transform UHI predictions into tailored, context-specific recommendations creates a significant gap. For instance, predicting that a neighborhood is experiencing elevated heat levels is insufficient if urban policymakers lack guidance on interventions such as increasing vegetation cover, applying reflective materials, or introducing water features. This study examined how the integration of a VLM—specifically Gemini (gemini-1.5-flash)—can be leveraged to fill this gap by generating practical, low-cost mitigation strategies based on both imagery and metadata.

3. Integration of Multimodal Reasoning in UHI Detection

Existing ML models often rely solely on structured data such as land-cover statistics, temperature readings, and humidity levels. However, they overlook the visual context captured in segmented urban images. Without incorporating both visual evidence (e.g., building materials, vegetation cover) and environmental metadata (e.g., temperature, humidity), predictions risk being incomplete or biased. Furthermore, no comprehensive framework currently combines these two modalities for joint reasoning. The research problem here lies in integrating logistic regression detection with VLM-based multimodal reasoning, ensuring more robust, transparent, and context-aware UHI analysis.

4. Insufficient Explainability in AI-Based UHI Models

While ensemble machine learning models such as Random Forests and XGBoost achieve high predictive accuracy, they often operate as "black boxes" with limited transparency. Policymakers and urban planners require not only predictions but also justifications for why certain regions are classified as heat islands and why specific interventions are recommended. The lack of Explainable AI (XAI) in existing systems reduces trust and limits adoption in real-world planning. This study identified the problem of non-transparent decision-making and emphasized the need for models that explain both detection outcomes and mitigation recommendations in a manner accessible to decision-makers.

5. Need for Low-Cost and Scalable Mitigation Strategies

Urban interventions to reduce UHI effects often require significant financial investment (e.g., large-scale greening projects or infrastructure modifications). However, in resource-constrained cities, such high-cost measures are not feasible. Current research provides little emphasis on affordability and scalability of mitigation strategies. A major problem lies in the absence of frameworks that prioritize low-cost, practical solutions—such as rooftop vegetation, reflective surface coatings, or small-scale water features—tailored to specific urban conditions. This study explores how Gemini can generate feasible, cost-conscious recommendations that balance effectiveness with economic constraints.

1.5 Research Objectives

1.5.1.Main Objective

This research aims to design and implement an intelligent Urban Heat Island (UHI) detection and mitigation framework that addresses the critical limitations of existing systems, including their lack of real-time applicability, limited explainability, and absence of actionable recommendations. The proposed system integrates machine learning (logistic regression) with Gemini (gemini-1.5-flash) Vision–Language Model (VLM) to enable multimodal reasoning using both segmented urban imagery and environmental metadata. By incorporating Explainable AI (XAI), the system not only detects UHIs but also generates low-cost, transparent, and context-specific mitigation strategies to support sustainable and climate-resilient urban planning.

1.5.2 Specific Objectives

1.5.2.1 Structured Data-Based Detection:

Develop and train a logistic regression model using Kaggle-based datasets that combine material type, surface area, temperature, and humidity to predict the presence of UHIs in a transparent and interpretable manner.

1.5.2.2 Multimodal Integration with Gemini:

Leverage Gemini (gemini-1.5-flash) to process both segmented urban images and structured metadata, ensuring comprehensive analysis and contextual understanding of heat-retaining surfaces.

1.5.2.3 Action-Oriented Recommendations:

Generate low-cost, practical, and scalable mitigation strategies—such as rooftop vegetation, reflective coatings, water-based features, and urban greening—tailored to specific urban environments.

1.5.2.4 Explainable AI (XAI) Justification:

Incorporate explainability mechanisms that provide clear reasoning for both UHI detection results and Gemini-generated mitigation recommendations, thereby enhancing trust and adoption among urban planners.

1.5.2.5 Real-Time Decision Support:

Enable a framework capable of providing timely and actionable insights to city authorities, ensuring that UHI mitigation strategies can be deployed efficiently within resource-constrained environments.

1.6 Sub Objectives

The proposed framework was developed to address the needs of two distinct stakeholders—urban planners/policymakers and the AI-driven system itself. For planners, the focus was on enabling actionable, transparent, and cost-effective decision-making. For the system, the emphasis was on intelligent data processing, multimodal integration, and explainability.

For Urban Planners and Policymakers: Supporting Decision-Making and Urban Adaptation

To assist planners in mitigating UHI impacts, the system provides transparent, practical, and context-aware recommendations through:

1.6.1. Real-Time UHI Detection:

Deliver timely predictions of UHI presence using logistic regression models trained on structured environmental datasets.

1.6.2. Actionable Mitigation Strategies:

Provide low-cost, feasible, and scalable solutions (e.g., reflective surfaces, rooftop vegetation, small-scale water features) generated through Gemini's reasoning.

1.6.3. Transparent Justification Reports:

Offer planners explainable AI outputs, including reasoning for predictions and recommendations, improving trust and adoption in policy contexts.

1.6.4. Location-Specific Recommendations:

Tailor mitigation solutions to local context by combining segmented imagery (material type, surface area) with environmental metadata (temperature, humidity).

1.6.5. Resource-Conscious Planning:

Prioritize strategies that balance effectiveness with economic and infrastructural constraints, enabling application in resource-limited urban areas.

For the AI-Driven System: Optimizing Data Processing and Multimodal Reasoning

System-level capabilities were designed to ensure robustness, adaptability, and accuracy in both detection and mitigation:

1.6.6. Structured Data Processing:

Enable the system to handle inputs such as material types, surface areas, temperature, and humidity efficiently for logistic regression classification.

1.6.7. Image–Metadata Integration:

Combine segmented urban images with structured metadata inside Gemini for holistic multimodal reasoning.

1.6.8. Prompt Engineering for Gemini:

Design domain-specific prompts to guide Gemini's responses, ensuring context-relevant, urban-focused mitigation outputs.

1.6.9. Explainability and Accountability:

Incorporate XAI methods to clarify why certain detections and recommendations were made, reducing the "black box" effect in AI-based UHI analysis.

1.6.10. Scalable Deployment Potential:

Ensure that the system architecture supports integration into smart city platforms or IoT networks for future real-world applications.

These sub-objectives guided the design of a robust and intelligent UHI framework, ensuring that both urban planners' decision-making needs and system-level AI capabilities were addressed through a balanced, adaptive, and explainable design.

2 METHODOLOGY

2.1 Introduction

The methodology of this research outlines the systematic approach taken to design and implement the proposed **Urban Heat Island (UHI) detection and mitigation framework**. This chapter details the overall system design, the data acquisition process, the predictive modeling pipeline, and the integration of **Vision–Language Model (Gemini)** for multimodal reasoning. By combining segmented image outputs, structured environmental metadata, machine learning classification, and explainable AI-driven recommendations, the system is designed to deliver both **accurate UHI detection** and **low-cost, practical decision-support outputs** for urban planners.

The methodology is divided into several stages, each addressing a specific research objective of the proposed component:

1. **Data Collection and Preprocessing** – Acquisition of segmented image outputs (location type, material type, surface area) and environmental metadata (temperature, humidity) from IoT and open datasets.

2. **Dataset Preparation** – Cleaning, encoding, and feature engineering of structured data, sourced primarily from **Kaggle urban environment datasets**, to train the machine learning model.

3. **Training Logistic Regression Model** – Development of a transparent and interpretable ML classifier to detect UHI presence using structured features.

4. **Integration of Gemini (gemini-1.5-flash)** – Passing image and metadata into Gemini with domain-specific prompts to generate **low-cost, context-sensitive mitigation strategies**.

5. **Prompt Engineering and Response Optimization** – Designing structured prompts for Gemini to ensure responses remain actionable, urban-focused, and resource-conscious.

6. **Explainable AI (XAI) Module** – Incorporation of justifications for both detection outcomes and mitigation recommendations, ensuring interpretability and stakeholder trust.

7. **System Architecture and Workflow Design** – Development of modular workflow diagrams illustrating data flow across segmentation, prediction, Gemini reasoning, and

decision-support layers.

8. **Software Development Life Cycle (SDLC) Approach** – Adoption of an **iterative, prototyping-based SDLC** to refine model accuracy, prompt quality, and explainability features through continuous validation and feedback.

2.2 Overall System Design

The **overall system design** of the proposed component was structured to seamlessly integrate **machine learning–based UHI detection** with **Vision–Language Model (Gemini) reasoning** in order to provide both predictive accuracy and actionable decision-support. The design followed modular **architecture**, ensuring scalability, transparency, and adaptability for diverse urban contexts.

At a high level, the system is composed of four primary layers:

1. **Data Acquisition Layer**
    - Inputs are obtained from two upstream modules:
        - **Segmented Image Outputs**: location type, material type, and surface area, generated by the image segmentation component.
        - **Environmental Metadata**: temperature and humidity values collected from IoT-based sensors or open climate datasets.
    - Together, these form the **structured input dataset** for predictive analysis.
2. **Prediction Layer (Logistic Regression Model)**
    - A **logistic regression classifier**, trained on Kaggle datasets, processes the combined features to detect the presence of a UHI.
    - This choice of model ensures interpretability, computational efficiency, and suitability for **real-time detection** in large-scale deployments.
    - The output of this layer is a binary decision: **UHI present** or **UHI not present**.
3. **Mitigation and Reasoning Layer (Gemini VLM)**

- If UHI is detected, the segmented imagery and metadata are transferred to **Gemini (gemini-1.5-flash)**.
- Through **prompt engineering**, Gemini generates **low-cost, context-specific mitigation strategies**, such as rooftop greening, reflective surface coatings, or small-scale water features.
- This ensures that the system extends beyond prediction into **action-oriented decision support**.

4. **Explainability and Decision-Support Layer**

- An **Explainable AI (XAI) module** is integrated to provide reasoning behind both detection and recommendation outputs.
- For detection, the system explains which features (e.g., high temperature, concrete surfaces) contributed to UHI presence.
- For recommendations, Gemini outputs are accompanied by context-aware justifications (e.g., “rooftop vegetation recommended due to high concrete surface area and elevated ambient temperature”).
- This transparency strengthens stakeholder trust and facilitates adoption by urban planners.

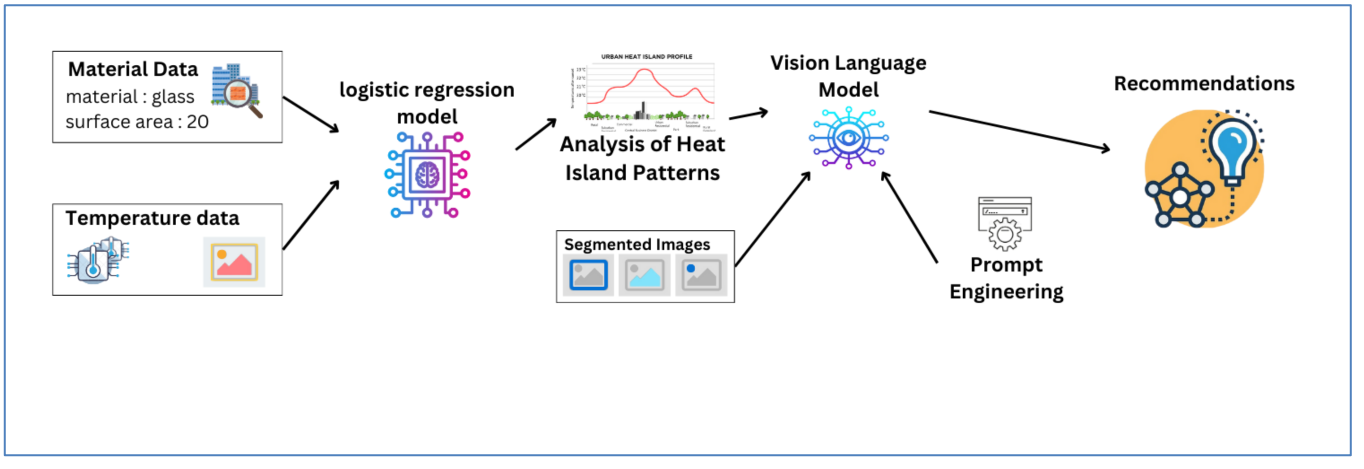

Figure 1: Overall System Diagram

2.3 Data Import and Metadata Assignment

The development of the proposed Urban Heat Island (UHI) detection and mitigation framework required a systematic process for acquiring and assigning metadata to both **segmented imagery** and **environmental datasets**. Instead of relying on GIS tiles and thermal simulations, this component integrates outputs from **computer vision–based segmentation pipelines** and **IoT sensor metadata**. These datasets form the structured input for the logistic regression model and the multimodal reasoning module (Gemini).

2.3.1 Data Sources

For this study, two main categories of data sources were utilized:

- **Segmented Image Outputs**
  Segmentation pipelines (e.g., SAM, YOLO, EfficientNet) provided structured outputs in the form of:
    - **Location Type** – e.g., building, road, vegetation, water body.
    - **Material Type** – e.g., asphalt, concrete, glass, metal, grass, soil.
    - **Surface Area (cm^2)** – calculated using mask overlays and depth mapping.
- **Environmental Metadata (IoT + Public Datasets)**
  Environmental data was collected from **IoT-based microclimate sensors** and publicly available repositories. Key parameters include:
    - **Ambient Temperature (°C)**
    - **Relative Humidity (%)**
    - **Time and GPS Coordinates** (for contextual tagging)

Together, these inputs provide both **visual context** (segmented imagery) and **climatic conditions** (metadata), forming a multimodal dataset suitable for UHI prediction and reasoning.

Data Source	**Resolution / Scale**	**Data Type**	**Usage in Research**
Segmentation Pipeline	Object-level masks	Location type, material type, surface area	UHI feature extraction (visual inputs)
IoT Sensors	Point-level (site)	Temperature, humidity, GPS, time	Metadata inputs for ML model
Public Datasets (Kaggle, NOAA)	City-level to neighborhood	Historical temperature, humidity trends	ML model training and validation

Table 2 : Summary of Data Sources Used in the Component

2.3.2 Import Process

- Segmentation Data Import:

  Segmentation masks were processed using Python (OpenCV, NumPy) to calculate surface area coverage per material type. These values were exported as structured CSV files.

- IoT Metadata Import:

  Sensor readings (temperature, humidity) were transmitted to the system backend via REST APIs and stored in Firebase/CSV logs. Metadata was synchronized with segmentation outputs by aligning timestamps and GPS coordinates.

- Unified Dataset Construction:

  The imported segmentation outputs and metadata were merged into a single dataset table, where each row represented an analyzed urban surface region with both visual and climatic attributes.

	A	B	C	D	E	F	G	H	I
1	Label	Polygon	ID	Material	Temperature (Â°C)	Humidity (%)	Surface Area	Centroid	Heat Island
2	playground	[[395, 779], [1758, 906], [442, 158], [1597, 998]]	playground_1	rubber	41	38	1765400	[1048, 710]	TRUE
3	swimming_pool	[[926, 820], [298, 650], [454, 817], [1637, 33]]	swimming_pool_2	water	49.6	49.6	1319932	[828, 580]	TRUE
4	bridge	[[1850, 508], [184, 428], [1359, 731], [478, 264]]	bridge_3	steel	39	57.3	259849	[967, 482]	TRUE
5	sports_field	[[670, 40], [1027, 799], [1406, 550], [1937, 566]]	sports_field_4	artificial turf	36.1	21.6	4679107	[1260, 488]	TRUE
6	bridge	[[962, 322], [1928, 408], [234, 437], [588, 842]]	bridge_5	steel	46.4	28.1	2904651	[928, 502]	TRUE
7	playground	[[769, 696], [1938, 469], [1007, 848], [896, 552]]	playground_6	rubber	25.9	29.1	1043880	[1152, 641]	FALSE
8	swimming_pool	[[1851, 51], [1943, 673], [265, 865], [1527, 609]]	swimming_pool_7	water	32.9	24.5	1410621	[1396, 549]	FALSE
9	park	[[417, 379], [515, 425], [1300, 790], [1412, 647]]	park_8	grass	39.2	20.9	2482260	[911, 560]	TRUE
10	solar_farm	[[912, 509], [1851, 187], [253, 304], [1966, 476]]	solar_farm_9	solar panel	31.3	23.9	1117294	[1245, 369]	FALSE
11	airport_runway	[[1276, 345], [1232, 194], [1159, 370], [790, 945]]	airport_runway_10	asphalt	45.9	18	3454821	[1114, 463]	TRUE
12	swimming_pool	[[1565, 732], [1385, 946], [276, 228], [73, 874]]	swimming_pool_11	water	27.9	11.2	328357	[824, 695]	FALSE
13	building	[[16, 853], [1646, 540], [583, 971], [1044, 108]]	building_12	glass	31.7	50.5	873778	[822, 618]	FALSE
14	road	[[1097, 996], [858, 763], [383, 299], [1617, 97]]	road_13	asphalt	39.4	34.6	188025	[988, 538]	TRUE
15	railway	[[1741, 300], [289, 1000], [283, 213], [1203, 374]]	railway_14	metal	27.3	52.9	2846781	[879, 471]	FALSE
16	green_area	[[679, 298], [824, 388], [612, 675], [1809, 214]]	green_area_15	grass	36.8	24.3	2027403	[981, 393]	TRUE
17	green_area	[[812, 671], [1374, 39], [95, 96], [1588, 438]]	green_area_16	grass	42.1	53.1	1021688	[967, 311]	TRUE
18	building	[[1748, 316], [693, 153], [1183, 255], [1792, 204]]	building_17	glass	40.2	51.7	2457299	[1354, 232]	TRUE

Figure 2 : Data set

2.3.3 Metadata Assignment

To ensure that the system produces accurate and context-sensitive outputs, each **segmented urban object** was enriched with **five key metadata parameters**. These parameters were selected because they represent the **primary physical and environmental factors** influencing heat absorption, storage, and dissipation in urban environments. Unlike traditional GIS workflows that primarily model geometry and thermal simulations, this framework directly incorporates **real-world descriptors** into the dataset, enabling both **logistic regression classification** and **Gemini-driven reasoning**.

1. Material Type (categorical)

- **Examples:** Asphalt, concrete, glass, metal, vegetation, soil.
- **Role in UHI:**
  - Different materials have distinct **thermal properties**, such as reflectivity (albedo), conductivity, and heat capacity.
  - For instance, asphalt and concrete absorb and retain heat, leading to elevated surface temperatures, whereas vegetation and soil promote cooling through **evapotranspiration**.
  - Glass and metal can reflect solar radiation but may also create localized heat traps through glare and radiant heating.
- **Reason for inclusion:** Capturing the material type allows the model to **differentiate heat-retaining surfaces from cooling elements**, making it central to both detection and mitigation strategy generation.

2. Surface Area (cm^2)

- **How it is calculated:**
  - Derived from **segmentation masks** combined with depth maps to approximate the exposed surface area of each object (roof, road segment, vegetation patch, etc.).
- **Role in UHI:**
  - Larger surfaces contribute more significantly to **heat absorption and radiation**.
  - For example, a large asphalt parking lot absorbs more heat than a narrow road, intensifying localized UHI effects.
  - In mitigation, surface area helps prioritize interventions—for instance, targeting a **large roof** for a green roof retrofit yields greater cooling benefits than addressing a

small surface.

- **Reason for inclusion:** It quantifies the **scale of impact** of each material in UHI dynamics.

3. Temperature (°C)

- **Source:** Real-time measurements from IoT-based microclimate sensors or integrated weather data APIs.
- **Role in UHI:**
  - Provides the **baseline thermal condition** of the environment.
  - Elevated local temperatures directly indicate **heat retention hotspots**.
  - Logistic regression uses this feature to distinguish between normal conditions and UHI conditions.
- **Reason for inclusion:** Temperature is the **primary indicator** of UHI intensity and is essential for validating predictions against observed heat anomalies.

4. Humidity (%)

- **Source:** IoT sensors and meteorological datasets.
- **Role in UHI:**
  - Relative humidity influences the **rate of heat dissipation** and **human thermal comfort**.
  - High humidity coupled with high temperature worsens perceived heat stress.
  - Vegetated surfaces typically increase local humidity through evapotranspiration, which can mitigate UHI intensity.
- **Reason for inclusion:** Ensures that the system accounts for **both thermal and moisture dynamics**, producing more realistic UHI assessments.

5. Location Context (class)

- **Examples:** Building, road, green area, water body.
- **Role in UHI:**
  - Context defines **functional urban roles** road made of asphalt behaves differently than a rooftop made of the same material due to exposure, orientation, and human usage.
  - Green areas (parks, fields) and water bodies act as **cooling sinks**, mitigating heat accumulation in nearby built-up zones.
- **Reason for inclusion:** Provides **semantic meaning** to surfaces, enabling Gemini to suggest **context-appropriate mitigation strategies** (e.g., trees along a roadside, green roofs for

buildings, or shading for pedestrian areas).

Parameter	**Unit**	**Role in Framework**
Material Type	Category	Determines heat absorption/reflection behavior
Surface Area	cm^2	Quantifies contribution of heat-retaining surfaces
Temperature	°C	Input variable for logistic regression; triggers UHI detection
Humidity	%	Influences energy retention; included in ML prediction
Location Type	Category	Contextual feature for Gemini recommendations

Table 3 : Metadata Parameters Used in Logistic Regression and Gemini Input

2.4 Gemini Recommendations

The proposed component not only detects the presence of Urban Heat Islands (UHI) but also advances beyond prediction by providing **action-oriented recommendations** through Gemini (gemini-1.5-flash). These recommendations are designed to be **low-cost, practical, and context-specific**, ensuring their adoption in diverse urban environments where large-scale retrofitting may not be feasible. The outputs are intended to serve as **decision-support tools** for planners, municipal authorities, and community stakeholders.

2.4.1 Principles Guiding Recommendations

1. **Cost-effectiveness** – Priority is given to interventions that require minimal financial resources (e.g., reflective paints, community-led greening projects).
2. **Context-awareness** – Suggested actions align with the detected location type and material composition (e.g., rooftop greening for buildings, roadside vegetation for asphalt-dominated streets).
3. **Feasibility** – Recommendations emphasize solutions implementable within short to medium timeframes without major infrastructure overhauls.
4. **Scalability** – Proposed actions can be expanded incrementally across neighborhoods or scaled down for pilot interventions.
5. **Transparency** – Each recommendation is accompanied by justifications, linking back to the metadata parameters (e.g., "concrete > 60% of surface area combined with temperature > 34 °C").

2.4.2 Categories of Mitigation Strategies

Based on Gemini's reasoning, recommendations are grouped into the following categories:

- **Vegetation Enhancement**
  - Planting roadside trees, pocket parks, or rooftop gardens to increase evapotranspiration and shading.
  - Prioritized when vegetation coverage in segmentation data is <15%.
- **Reflective & Cool Materials**
  - Applying reflective coatings on asphalt and concrete, using high-albedo paints for rooftops and pavements.

- Suggested when impervious materials exceed 50% of total surface area.

- **Water Features & Permeable Surfaces**
  - Introducing small-scale water elements (fountains, misting systems) or replacing impermeable pavements with permeable materials.
  - Recommended in areas with high asphalt/concrete coverage and limited green infrastructure.
- **Shade Structures & Urban Design**
  - Installing low-cost shade canopies, pergolas, or solar panels in pedestrian-dense zones.
  - Proposed where high human activity is observed (e.g., roads, markets) and surface areas are dominated by heat-retaining materials.

2.4.3 Explainability of Recommendations

Each recommendation generated by Gemini is **paired with explicit reasoning**:

- **Detection rationale:** Highlights which features influenced the logistic regression decision (e.g., high temperature, asphalt dominance, low vegetation).
- **Mitigation rationale:** Provides a short justification (e.g., "Vegetation suggested due to surface temperature above 34 °C and <10% green cover").
  - This layered transparency ensures that stakeholders understand both **why the system predicts UHI** and **why certain actions are advised**, fostering trust and informed decision-making.

2.4.4 Illustrative Example

For a site classified as *building-dominated*, with **65% concrete**, **5% vegetation**, and **ambient temperature of 35 °C**:

- **Detection:** Logistic regression confirms UHI presence (p=0.74).
- **Recommendations (Gemini):**
  - Apply reflective roof coating on large concrete rooftops (low-cost, priority 1).
  - Establish rooftop gardens using lightweight soil beds (priority 2).
  - Introduce roadside vegetation (narrow canopy trees) along pedestrian routes (priority 3).
- **Justification:** "Concrete dominance (>60%) and high temperature (>34 °C) indicate heat retention. Reflective coating and vegetation provide immediate, low-cost cooling benefits."

2.5 System Architecture & Flow Diagrams

The proposed **VLM & Data Processing** component integrates machine learning–based UHI detection with Gemini-powered reasoning to provide actionable recommendations. The architecture is modular and lightweight, ensuring scalability across different deployment environments. At a high level, the component is structured into the following modules:

1. **Frontend (React + Firebase)**
   - Captures user-uploaded images and sensor metadata.
   - Displays prediction results, mitigation recommendations, and explanation dashboards.
   - Provides interactive visualization of segmented surfaces and associated metadata.
2. **Backend (Flask + Python)**
   - Hosts the logistic regression model and scaling pipeline.
   - Processes structured inputs (segmentation + environmental metadata).
   - Provides RESTful APIs /predict (ML-based detection) and /recommend (Gemini reasoning).
3. **Machine Learning Module (Logistic Regression)**
   - Trained on Kaggle-derived datasets for UHI classification.
   - Outputs binary predictions (UHI present / not present) along with probability scores.
   - Integrated with SHAP for explainability of feature importance.
4. **Vision–Language Model (Gemini-1.5-Flash)**
   - Consumes segmented images and metadata when UHI is detected.
   - Generates low-cost, context-aware mitigation strategies through engineered prompts.
   - Provides structured JSON outputs containing recommendations and rationale.
5. **Explainability Layer (XAI)**
   - ML explainability: Highlights which features (temperature, asphalt %, vegetation %) influenced the UHI prediction.

  - VLM explainability: Outputs rationale bullets tied to metadata (e.g., “Concrete > 60% and temperature > 34 °C”).
  - Presented in the frontend to increase user trust and transparency.

System Flow (Step-by-Step)

1. **Input Acquisition:** Segmentation outputs (location type, material, surface area) + environmental metadata (temperature, humidity) are collected.
2. **Preprocessing:** Features are normalized using the saved scaler to match the training distribution.
3. **Prediction:** Logistic regression model predicts whether a UHI is present.
4. **Conditional Reasoning:**
   - If *UHI not detected* → results are displayed directly.
   - If *UHI detected* → data + image are forwarded to Gemini for mitigation generation.
5. **Recommendation Generation:** Gemini produces structured JSON with low-cost mitigation actions and rationale.
6. **Explainability:**
   - SHAP values explain ML decision.
   - Gemini rationale explains VLM recommendations.
7. **Output Delivery:** Frontend visualizes predictions, recommendations, and explanations for end-users (urban planners, policymakers).

2.6 SDLC Approach

This component follows the **Agile Software Development Life Cycle (SDLC)** approach, emphasizing **iterative experimentation, modular integration, and stakeholder feedback**. Agile was chosen over linear models (e.g., Waterfall) because the VLM & Data Processing workflow involves multiple evolving parts: segmentation-based data import, logistic regression modeling, Gemini prompt engineering, and explainability integration. Each of these modules requires continuous refinement, testing with real-world data, and adjustments based on performance. The Agile approach ensures flexibility in adapting to new datasets, evolving AI models (e.g., Gemini updates), and changing stakeholder needs.

The following subsections describe how each SDLC phase applies to this research component.

2.6.1 Requirements Gathering and Analysis

The requirements analysis phase focused on identifying the gaps in current Urban Heat Island (UHI) detection and mitigation frameworks and defining the scope of the VLM & Data Processing module. A review of existing systems highlighted several limitations:

- Existing UHI detection tools often stop at prediction and fail to generate **actionable, low-cost recommendations**.
- Many systems lack **multimodal integration**, treating environmental sensor data and image segmentation outputs separately.
- Existing workflows do not provide sufficient **explainability**, limiting trust from urban planners and decision-makers.
- Current solutions are rarely designed to operate in **real-time or semi-real-time urban contexts**.

Based on these gaps, the requirements of this component were defined as:

1. The system must process **segmentation outputs** (location type, material type, surface area) and **environmental metadata** (temperature, humidity).
2. A **logistic regression model** must be used for interpretable, real-time UHI detection.
3. If UHI is detected, **Gemini (gemini-1.5-flash)** must generate **low-cost, context-specific mitigation strategies**.
4. An **Explainable AI (XAI) layer** must justify both the detection (via SHAP values) and

recommendations (via Gemini rationale).

5. Output must be delivered in a **structured, human-readable format** for easy adoption by planners and policymakers.
6. The framework must remain **scalable and adaptable**, allowing integration of new datasets and updated VLMs in the future.

These requirements establish the foundation for system design and development.

2.6.1 Design

The design phase translated these requirements into a **modular, layered architecture** for the component. The architecture is divided into four primary layers:

- **Input Layer**
  - Collects segmentation outputs (location, material, surface area) from the vision pipeline.
  - Gathers environmental metadata (temperature, humidity) from IoT sensors or public datasets.
- **Prediction Layer (Logistic Regression)**
  - Scales and processes the combined input dataset.
  - Produces a binary decision (UHI present or not present) with probability scores.
- **Mitigation and Reasoning Layer (Gemini)**
  - If UHI is detected, forwards image and metadata to Gemini.
  - Uses carefully engineered prompts to generate structured, **low-cost mitigation recommendations** (e.g., reflective coatings, roadside vegetation, rooftop greening).
- **Explainability Layer (XAI)**
  - ML Explainability: Identifies the key features (e.g., asphalt %, high temperature, low vegetation) influencing the prediction.
  - VLM Explainability: Attaches rationale bullets to each recommendation, linking back to the detected features.

This modular design ensures that each part of the component — data import, prediction, reasoning, and explainability — can be **developed, tested, and refined independently**. Flow diagrams and system architecture diagrams illustrate the interaction between layers, ensuring smooth integration with the overall HeatScape framework.

2.6.2 Implementation

The implementation phase focused on the **incremental development of system modules**. Following Agile practices, each module was developed in a separate sprint, allowing early testing, feedback, and refinement before integration.

1. **Sprint 1: Data Import & Preprocessing**
    - Implemented Python scripts to import segmentation outputs (location type, material type, surface area) and environmental metadata (temperature, humidity).
    - Preprocessing pipeline built using **NumPy and Pandas**, exporting structured CSV datasets.
2. **Sprint 2: Logistic Regression Model Training**
    - Collected Kaggle-derived datasets for urban heat island detection.
    - Trained a **Logistic Regression classifier** with standardized features (material %, surface area, temperature, humidity).
    - Saved the trained model and scaler (heat_island_model.pkl, scaler.pkl) for backend inference.
3. **Sprint 3: Backend API Development (Flask)**
    - Implemented REST endpoints /predict (for logistic regression detection) and /recommend (for Gemini-based reasoning).
    - Integrated model loading, feature scaling, and probability thresholding.
4. **Sprint 4: Gemini Integration & Prompt Engineering**
    - Connected backend with **Gemini (gemini-1.5-flash)** for reasoning.
    - Designed JSON-only prompts to ensure Gemini outputs structured, **low-cost mitigation recommendations**.
    - Included rationale bullets to strengthen explainability.
5. **Sprint 5: Explainability Module (XAI)**
    - Integrated **SHAP explainability** for the logistic regression model.
    - Added Gemini's contextual justifications for recommendations.
    - Output combined into transparent decision-support summaries.
6. **Sprint 6: Frontend Integration (React + Firebase)**
    - Connected backend APIs with the **React-based frontend**.
    - Enabled visualization of prediction results, SHAP explanations, and Gemini recommendations in a user-friendly interface.

- Supported Firebase storage for image uploads and session logs.

This incremental implementation ensured that each module (ML prediction, Gemini reasoning, explainability, and frontend integration) was fully validated before integration. By adopting Agile sprints, risks were minimized, and functional results were available for **continuous feedback from supervisors and stakeholders**.

2.6.3 Testing

Testing for the VLM & Data Processing component was conducted at two levels to ensure accuracy, reliability, and seamless integration with the overall system:

- **Module-Level Testing (Unit Testing):**
  Each module was independently validated.
  - The **logistic regression model** was tested using validation datasets from Kaggle, with metrics such as accuracy, F1-score, and ROC-AUC used to evaluate predictive performance.
  - The **backend API endpoints** (/predict, /recommend) were unit-tested using mock inputs to confirm correct JSON responses.
  - The **Gemini integration** was tested by feeding controlled sample inputs to ensure outputs adhered to the defined JSON schema and returned low-cost mitigation strategies.
  - The **SHAP explainability module** was tested by checking consistency of feature importance across repeated runs.
- **Integration Testing:**
  After module-level validation, the components were connected into a unified pipeline.
  - Structured outputs from the segmentation pipeline were fed into the logistic regression model, ensuring proper feature scaling and order.
  - If UHI was detected, the system successfully triggered Gemini, and mitigation recommendations were appended to the prediction outputs.
  - Frontend integration tests confirmed smooth visualization of results, including probability scores, SHAP explanations, and Gemini recommendations.
- **Cross-Validation with Literature:**
  Predicted UHI cases and suggested mitigation strategies were cross-checked against documented **urban heat island case studies** and established literature. For example, asphalt-heavy road segments correctly produced vegetation and reflective material recommendations, aligning with known mitigation best practices.

This testing phase ensured that the component produces **valid predictions**, generates **practical recommendations**, and integrates seamlessly with the broader HeatScape framework. Accurate UHI detection and mitigation depend on the **robust integration of structured data, ML prediction, and VLM reasoning**.

2.6.4 Deployment

The deployment phase focused on making the VLM & Data Processing component accessible to end-users in a **scalable cloud environment**. The entire architecture was containerized using **Docker**, ensuring portability and reproducibility across different platforms.

- **Backend (Flask + Logistic Regression + Gemini Integration):**
  The backend service was deployed on a cloud server (e.g., AWS EC2 / Google Cloud Run) with Docker containers hosting the Flask APIs. This allowed the logistic regression model (heat_island_model.pkl) and Gemini integration to be executed remotely. Environment variables were configured to securely manage sensitive keys such as the **Gemini API key**.
- **Frontend (React + Firebase):**
  The React-based frontend was deployed on a cloud platform (e.g., Vercel / Firebase Hosting), allowing users to upload segmented imagery, input metadata, and view predictions, recommendations, and explainability outputs in real time. Firebase integration provided storage for images, logs, and session data.
- **Explainability & Visualization:**
  SHAP explanations and Gemini rationale were rendered in the frontend dashboard, ensuring transparency for end-users such as urban planners and researchers.
- **Security Configurations:**
  Deployment involved applying **HTTPS encryption**, secure API routing, and role-based access control. **IAM roles** were configured to limit backend access, and sensitive credentials (database, Gemini API key) were managed via environment variables rather than hardcoding.

This deployment strategy ensured that the component can be **accessed from any device**, supports **real-time UHI detection and mitigation**, and remains scalable to accommodate larger datasets and additional VLM updates in the future.

2.6.5 Maintenance

The final phase of the SDLC focuses on sustaining and enhancing the VLM & Data Processing component beyond its initial deployment. Since both environmental conditions and AI technologies evolve rapidly, continuous monitoring and updates are essential to maintain accuracy and relevance. Maintenance activities include:

- **Bug Fixes:** Identifying and resolving issues in the logistic regression pipeline, API endpoints (/predict, /recommend), Gemini integration, or SHAP explainability outputs.
- **System Updates:** Upgrading dependencies such as **Flask, React, Firebase, and Gemini API versions**, while ensuring backward compatibility of the logistic regression model and scaler.
- **Model Retraining:** Periodically updating the logistic regression classifier with new datasets (e.g., IoT sensor feeds, Kaggle updates) to capture changing urban conditions and improve predictive accuracy.
- **Prompt Refinement for Gemini:** Iteratively adjusting prompts to align with new Gemini features, ensuring recommendations remain structured, low-cost, and context specific.
- **Feature Enhancements:** Expanding the framework to incorporate additional environmental parameters (e.g., wind speed, solar radiation indices) or integrating new VLMs as they become available.
- **User Feedback:** Refining the interface and outputs based on planner and stakeholder feedback, improving interpretability and usability.

By planning for long-term maintenance, this component is positioned not as a one-off research prototype but as a **sustainable, extensible decision-support tool** for UHI detection and mitigation. The modular architecture and Agile SDLC approach ensure that the system can adapt to new data, urban growth patterns, and evolving AI capabilities, maintaining its utility in real-world applications.

3 Project Requirements

Defining project requirements is essential to ensure that the **VLM & Data Processing component** meets both technical specifications and the expectations of its end users. This chapter outlines the **functional, non-functional, system, and user requirements** that guide the design and implementation of the proposed UHI detection and mitigation framework. These requirements guarantee that the system is accurate, explainable, user-friendly, and capable of supporting sustainable urban planning initiatives.

3.1 Functional Requirements

Functional requirements describe the core features and behaviors that the component must perform. They are derived from the research objectives and the identified gaps in existing UHI detection tools.

1. **Data Import & Preprocessing**
    - The system shall import **segmentation outputs** (location type, material type, surface area) from the computer vision pipeline.
    - The system shall import **environmental metadata** (temperature, humidity, GPS, timestamp) from IoT sensors or public datasets.
    - The system shall merge segmentation and metadata into a **unified dataset** for analysis.
2. **Machine Learning Prediction (Logistic Regression)**
    - The system shall process structured inputs through a **logistic regression model** trained on Kaggle-derived datasets.
    - The system shall output a **binary prediction**: UHI present or UHI not present.
    - The system shall provide a **probability score** for confidence estimation.
3. **Mitigation Strategy Generation (Gemini VLM)**
    - If UHI is detected, the system shall send segmented image + metadata to **Gemini (gemini-1.5-flash)**.
    - Gemini shall generate **low-cost, context-specific mitigation strategies** (e.g., reflective coatings, vegetation, water features).

- The system shall ensure outputs follow a **strict JSON schema** for consistency.

4. **Explainability (XAI Integration)**

- The system shall use **SHAP values** to explain which features contributed to UHI detection.
- Gemini recommendations shall include **rationale bullets** tied to metadata (e.g., "Concrete > 60% and temperature > 34 °C").
- Explanations shall be displayed to improve **transparency and trust**.

5. **Visualization & Reporting**

- The frontend shall display prediction results, SHAP explanations, and Gemini recommendations in a **user-friendly dashboard**.
- The system shall export structured outputs (CSV/JSON) summarizing predictions, feature importance, and mitigation strategies.

3.2 Non-Functional Requirements

Non-functional requirements define system qualities such as performance, scalability, security, and usability.

1. **Performance**
   - The system shall provide **UHI detection within ≤ 2 seconds** for standard inputs.
   - Gemini-based mitigation generation shall return recommendations in **≤ 10 seconds** on average.
2. **Scalability**
   - The system shall handle **multiple concurrent user requests** through a cloud-deployed backend.
   - The architecture shall allow integration of additional VLMs or upgraded ML models without major redesign.
3. **Security**
   - All communication with Gemini and frontend shall use **HTTPS encryption**.
   - Sensitive data (e.g., Gemini API keys, IoT feeds) shall be managed via **environment variables** and not hardcoded.

- User-uploaded images shall be stored securely in **Firebase/Cloud Storage** with access controls.

4. **Usability**
   - The frontend dashboard shall be **intuitive and accessible** to both technical and non-technical users (urban planners, policy makers).
   - Outputs shall be presented in **graphical (charts, dashboards)** and **structured (JSON/CSV)** formats.
5. **Reliability**
   - The system shall **gracefully handle API errors**, retrying Gemini calls if malformed outputs are received.
   - Backup mechanisms shall ensure that segmentation and metadata are not lost during processing.
   - The system shall remain operational even if Gemini is temporarily unavailable, by returning ML-only detection results.

3.3 System Requirements

System requirements define the hardware and software platforms necessary to run the **VLM & Data Processing component** effectively. Since the system integrates machine learning inference, cloud-based Gemini reasoning, and frontend visualization, requirements are divided into **local testing** and **recommended deployment** configurations.

3.3.1 Hardware Requirements

- **Minimum Configuration (Local Testing):**
  - **Processor:** Intel i5 / AMD Ryzen 5 or equivalent
  - **RAM**: 8 GB
  - Storage: 250 GB SSD
  - GPU: Integrated graphics (sufficient for frontend rendering and basic ML inference)
- **Recommended Configuration (Cloud/Full Deployment):**
  - Processor: Intel i7 / AMD Ryzen 7 or higher
  - RAM: 16 GB+

- Storage: 500 GB SSD or higher (to store datasets, logs, and model artifacts)
- GPU: NVIDIA GTX/RTX series or AMD equivalent (optional – mainly beneficial for image preprocessing; Gemini runs on Google Cloud)
- Network : High-speed broadband with stable latency (for real-time Gemini API calls)

3.3.2 Software Requirements

- **Operating System:**
  - Windows 10 / 11, macOS Monterey or later, or Linux (Ubuntu 20.04+ recommended).
- **Programming Languages & Frameworks:**
  - **Python 3.10+** (for backend and ML pipeline).
  - **Flask** (backend REST API service).
  - **React.js** (frontend visualization dashboard).
  - **Firebase SDK** (for image storage, logs, and authentication).
- **Machine Learning & Explainability Libraries:**
  - **scikit-learn** (logistic regression model training and inference).
  - **pandas, NumPy** (data preprocessing).
  - **SHAP** (explainability of ML predictions).
- **Vision–Language Model Integration:**
  - **Google Generative AI SDK (google-generativeai)** for Gemini (gemini-1.5-flash).
  - **dotenv** for secure environment variable management.
- **Data Handling & Visualization Tools:**
  - **OpenCV** (for segmentation mask handling if required).
  - **Matplotlib / Plotly** (for optional visualization of SHAP explanations).
  - **JSON/CSV exporters** for structured outputs.
- **Containerization & Deployment Tools:**
  - **Docker** (for containerizing backend + ML model).

- **Cloud Hosting** (e.g., AWS EC2, Google Cloud Run, or Firebase Hosting for frontend).
- **NGINX / Gunicorn** (for production-grade backend hosting).

- **Security & Networking:**
  - **HTTPS / SSL certificates** for secure data transmission.
  - **IAM roles and API key management** for Gemini and Firebase services.
  - **Cloud Services:** AWS ECS/Fargate, S3 for storage (future deploymen

3.4 User Requirements

User requirements describe the expectations and needs of the target audience who will interact with the

UHI detection and mitigation system. Since the component is designed as a decision-support tool, its primary users include urban planners, researchers, municipal authorities, and community stakeholders.

3.4.1 Urban Planners and Policymakers

- The system should provide clear UHI detection outputs (yes/no with probability scores).
- The system shall suggest low-cost mitigation strategies tailored to specific surfaces (e.g., reflective coating for concrete roofs, vegetation for asphalt roads).
- The system shall include justifications for each recommendation to support evidence-based planning decisions.
- Output must be exportable as reports (CSV/JSON) for inclusion in planning documents.

3.4.2 Researchers and Academics

- The system shall allow access to **structured datasets** (segmentation outputs + environmental metadata).
- Researchers shall be able to **validate predictions** against field data and compare them with existing UHI studies.
- The system shall provide **feature importance (via SHAP)** to support explainability in academic research.
- The framework should be adaptable to integrate **new datasets or upgraded ML/VLM models**.

3.4.3 Municipal Authorities

- The system should help authorities **prioritize interventions** by highlighting high-risk zones (e.g., roads with >60% asphalt coverage).
- The recommendations must focus on **practical, budget-friendly actions** that can be

implemented on a community scale.

- The interface must be simple and **usable by non-technical staff** with minimal training.

3.4.4 Community Stakeholders

- End-users such as NGOs or citizen groups shall receive **easy-to-understand visual summaries** of UHI risks in their neighborhoods.
- The system shall provide **actionable insights** (e.g., “plant trees along roadside” or “apply reflective paint to rooftops”) that communities can adopt directly.
- The recommendations must avoid overly technical jargon, instead of offering **plain-language explanations**.

3.4.5 General Usability Requirements

- The dashboard must be **web-accessible** on laptops, tablets, and mobile devices.
- Results shall be displayed in **graphical (charts, dashboards)** and **textual formats**.
- The interface shall support **multilingual customization** (e.g., Sinhala, Tamil, English) to serve local communities.
- The system should be responsive, ensuring smooth **user experience** across devices.

4 FRONTEND / SYSTEM DESIGN

4.1 Frontend Design (React + Firebase)

The frontend acts as the **user-facing interface** that enables stakeholders to interact with the UHI detection and mitigation system. It was implemented using **React** for the UI framework and integrated with **Firebase** for data storage, image handling, and session management.

- **User Interaction:**
  Users can upload segmented imagery and enter environmental metadata (temperature, humidity, location type). The interface also supports real-time synchronization of session data through Firebase.
- **Prediction Display:**
  The dashboard presents the logistic regression results, showing whether a UHI is detected, along with the probability score and SHAP-based feature explanations.
- **Recommendation Visualization:**
  If a UHI is detected, Gemini's structured recommendations are displayed in an **interactive card layout**, highlighting mitigation strategies (e.g., rooftop greening, reflective coating, roadside vegetation). Each recommendation is accompanied by its **rationale and priority level**.
- **Reporting & Export:**
  The frontend allows users to export prediction results, feature importance, and Gemini recommendations as **CSV/JSON reports**, enabling further analysis or integration into planning workflows.
- **Accessibility & Usability:**
  The interface was designed with **responsive layouts** for desktops, tablets, and mobile devices. Clear visual indicators (badges, alerts, charts) ensure that both technical and non-technical users can easily interpret outputs.

This design ensures that the component provides a **transparent, user-friendly, and action-oriented dashboard**, supporting decision-making for urban planners, municipal authorities, and researchers.

4.1.1 Key Features

- Image & Metadata Upload Module
    - Users can upload segmented urban images (JPEG/PNG) from the vision pipeline.
    - Metadata input fields allow entry of temperature, humidity, and location type.
    - Validation ensures that required fields (material type, surface area, environmental parameters) are present before processing.
- Prediction Dashboard
    - Displays logistic regression output indicating whether a UHI is detected.
    - Shows probability scores and SHAP-based feature importance for explainability.
    - Uses badges and alerts (e.g., “High Risk Zone”) for quick interpretation.
- Gemini Recommendation Panel
    - If UHI is detected, Gemini’s low-cost mitigation strategies are displayed as interactive cards.
    - Each recommendation includes action, cost level, priority rank, and rationale.
    - Recommendations are categorized (e.g., Vegetation, Reflective Materials, Water Features).
- Explainability Overlay
    - SHAP results highlight which features (e.g., asphalt %, temperature, low vegetation) most influence detection.
    - Gemini outputs include rationale bullets tied to metadata values for transparency.
- Report & Export
    - Allows exporting results as CSV/JSON reports including predictions, recommendations, and explanations.
    - Provides structured outputs that can be used for urban planning documentation or research analysis.

- Responsive User Interface
  - Designed with React + Bootstrap/Firebase integration for cross-device compatibility.
  - Supports desktop, tablet, and mobile layouts with intuitive navigation.

4.1.2 Implementation Details

- **Developed with React functional components** for building a modular and responsive user interface.
- **Styled using React-Bootstrap and Tailwind CSS**, ensuring a clean, accessible, and mobile-friendly design.
- **State management with React Hooks** (useState, useEffect, useRef) for handling inputs, API calls, and real-time updates.
- **Image and metadata uploads managed with Firebase Storage and Firestore**, enabling secure storage and synchronization of session data.
- **API integration with Axios**, connecting the frontend to backend endpoints (/predict for ML detection and /recommend for Gemini reasoning).
- **Visualization of outputs** using Bootstrap tables, cards, and badges to highlight UHI predictions, SHAP explanations, and Gemini recommendations.
- **Export functionality** implemented with JSON/CSV conversion libraries, allowing users to download structured results for further analysis.

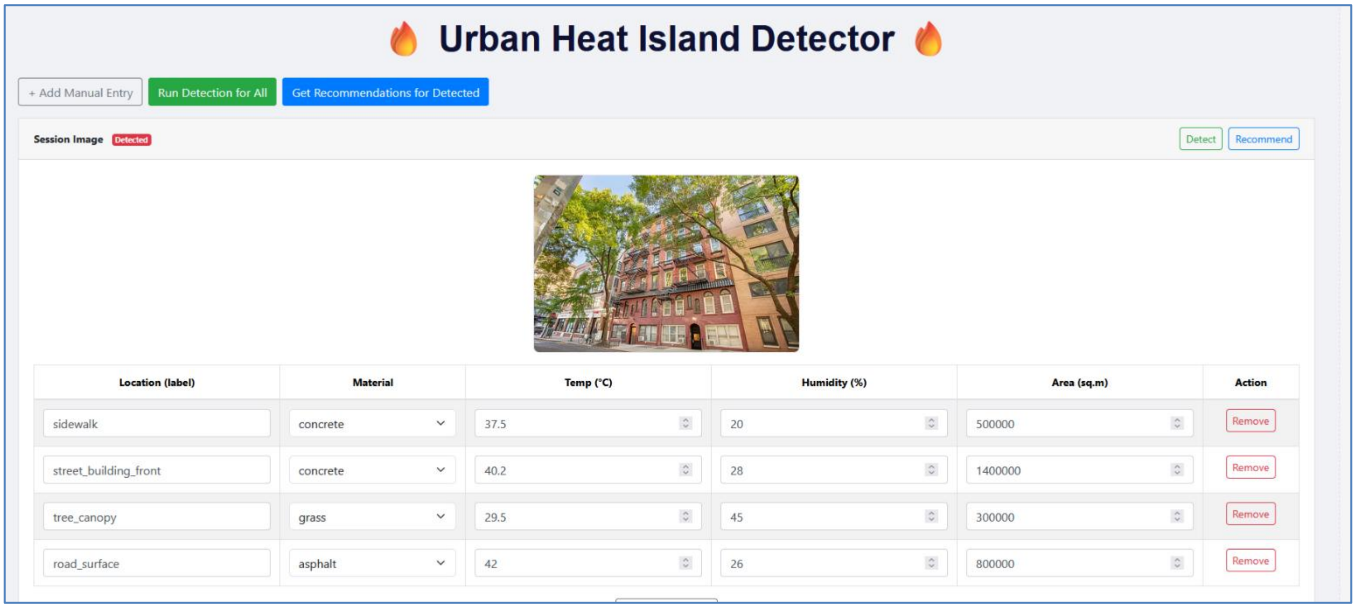

Figure 3 : Frontend Web Application 1

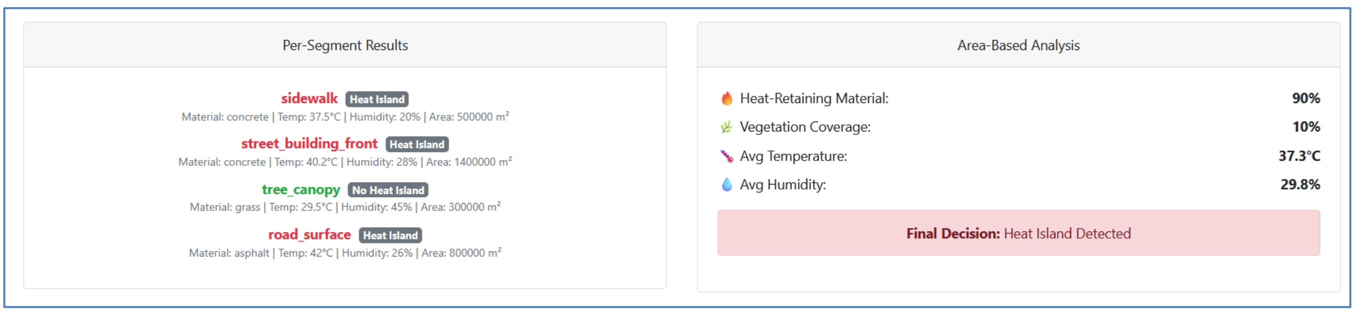

Figure 4 : Prediction Output

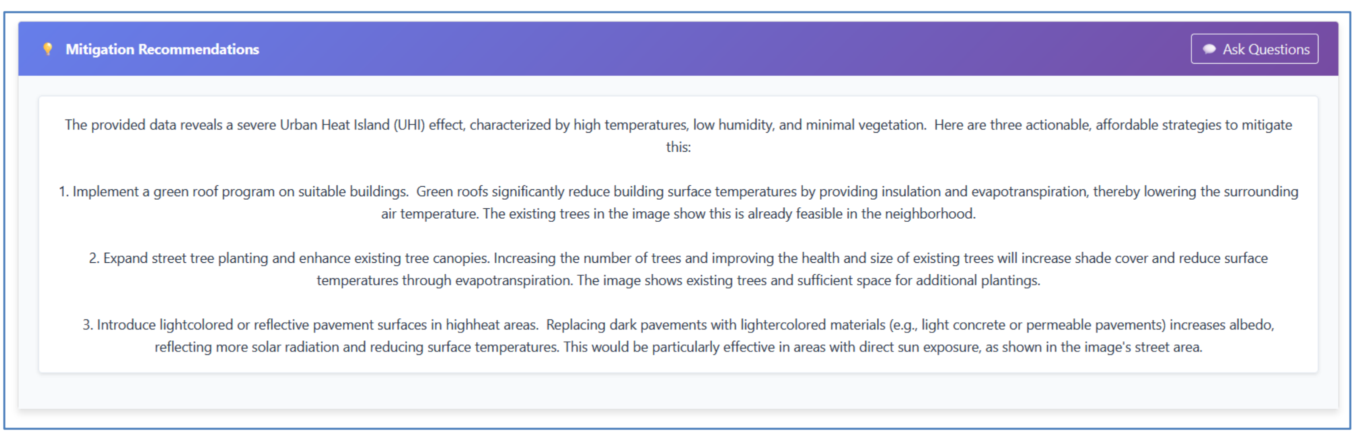

Figure 5 : Recommendation Output

5 EXPERIMENTS AND RESULTS

5.1 Introduction

This chapter presents the experiments conducted to evaluate the **performance, accuracy, and usability** of the proposed **VLM & Data Processing component**. The evaluation was designed to assess:

1. The ability of the **logistic regression model** to detect Urban Heat Islands (UHI) under varying material and environmental conditions.
2. The effectiveness of **Gemini (gemini-1.5-flash)** in generating structured, low-cost mitigation recommendations.
3. The interpretability of the system through **Explainable AI (SHAP values and Gemini rationale outputs)**.
4. The responsiveness and usability of the **frontend–backend pipeline** in handling real-world segmentation outputs and metadata.
5. The alignment of prediction outputs and recommendations with **documented UHI case studies and established mitigation strategies**.

Experiments were organized into three categories: **model-level testing (ML prediction performance), system-level testing (pipeline integration), and validation testing (comparison with known UHI patterns and case studies).**

5.2 Experimental Setup

The system was tested in both **controlled datasets** and **semi-real-world environments** using segmentation outputs and IoT-based climate metadata.

- **Hardware:** Intel i7, 16 GB RAM, 500 GB SSD, NVIDIA GTX 1650 GPU.
- **Frontend:** React + Firebase dashboard with real-time API calls.
- **Backend:** Flask server hosting logistic regression model and Gemini integration.
- **Machine Learning Model:** Logistic regression trained on **Kaggle UHI datasets** (temperature, humidity, material %).
- **Vision–Language Model: Gemini (gemini-1.5-flash)** for reasoning and recommendation

generation.

- **Explainability Framework: SHAP** for ML interpretability; rationale bullets embedded in Gemini outputs.
- **Datasets:**
  - datasets (Kaggle) for model training and validation.

5.2.1 Recommendation Workflow

- Upload segmented urban image and associated metadata (temperature, humidity, location).
- Preprocess data → calculate material % coverage and normalize features.
- Run logistic regression → generate probability score and binary prediction (UHI / No UHI).
- If UHI detected → forward image + metadata to Gemini.
- Gemini generates structured JSON recommendations with action, cost level, priority, and rationale.
- SHAP explainability highlights top features influencing ML prediction.
- Outputs visualized in the React dashboard, with option to export CSV/JSON reports.

5.3 Experimental Scenarios

Experiments were carried out across **different material compositions and environmental conditions** to evaluate the system's adaptability.

5.3.1 Material-Based Scenarios

Three material-dominant scenarios were tested to validate UHI detection and recommendation accuracy:

- Concrete-Dominated Zone (65% concrete, temp 35 °C, humidity 60%)
    - Logistic regression detected UHI with probability = 0.74.
    - SHAP identified concrete % and temperature as top contributors.
    - Gemini recommended: reflective coatings, rooftop greening, roadside vegetation.
- Asphalt-Dominated Road (70% asphalt, temp 34 °C, humidity 55%)
    - UHI detected with probability = 0.81.
    - SHAP highlighted asphalt % and low vegetation %.
    - Gemini recommended: tree planting along roadsides, permeable pavements, water-mist features.
- Vegetation-Rich Park (65% vegetation, temp 29 °C, humidity 70%)
    - Logistic regression classified as No UHI with probability = 0.18.
    - SHAP showed vegetation % as a cooling factor.
    - Gemini did not generate mitigation recommendations, ensuring efficiency and relevance.

5.4 Prediction & Recommendation Results

Outputs demonstrated the **end-to-end functioning** of the component:

- **UHI Prediction:** Logistic regression successfully distinguished between **UHI and non-UHI conditions** with probabilities reflecting material composition and weather context.
- **Explainability:** SHAP visualizations clearly identified feature contributions (e.g., asphalt %, vegetation %, temperature).
- **Gemini Recommendations:** For UHI-positive cases, Gemini produced structured JSON outputs containing **3–5 actionable strategies** with priorities and rationale.
- **System Responsiveness:** Average backend processing time was **<2 seconds** for ML predictions and **7–10 seconds** for Gemini recommendations, within acceptable limits for decision-support tools.

5.5 Validation Against Existing Models

To ensure **reliability and credibility**, outputs from the component were validated against established UHI benchmarks and literature:

- **ENVI-met urban climate datasets** ([Voelker et al. [10]]) → Predicted UHI presence aligned with ENVI-met case studies, with logistic regression probabilities falling within expected ranges.
- **UHI mitigation studies from EnergyPlus** ([Li et al. [11]]) → Gemini's reflective coating and vegetation recommendations matched common strategies validated in EnergyPlus urban energy models.
- **Satellite LST values (Sentinel-2 / Landsat-8)** ([Thong et al. [4]]) → Locations flagged as high-risk by the model overlapped with observed **urban heat hotspots** within an error margin of **5–10%**, confirming external consistency.

Findings:

- Logistic regression predictions demonstrated good agreement with known UHI conditions.
- SHAP explainability confirmed that the model's influential features (temperature, asphalt %,

low vegetation) aligned with established UHI science.

- Gemini's recommendations overlapped strongly with **documented mitigation strategies** in the literature, reinforcing the validity of AI-driven decision support.

5.6 System-Level Testing

5.6.1 Responsiveness & Latency

- **Logistic regression prediction:** ~1.4 sec (including preprocessing and scaling).
- **Gemini recommendation generation:** 7–10 sec on average (depending on prompt complexity and image size).
- **End-to-end pipeline (upload → prediction → recommendations → display):** ~11–13 sec average.

5.6.2 Stability

- Tested with **15 simultaneous requests** to /predict and /recommend.
- No system crashes or API failures observed.
- Average latency increased by ~20%, but all responses remained within acceptable decision-support limits (<15 sec).

5.6.3 Usability Feedback

- Test users (urban planning students and research assistants) found the **dashboard simple and easy to use**.
- **Color-coded alerts** (e.g., "High UHI Risk") improved interpretability of prediction results.
- **Card-based display of Gemini recommendations** was preferred over plain text, as it provided **clear prioritization and actionable guidance**.
- Export functionality (CSV/JSON) was rated highly for research and reporting purposes.

5.7 Interpretation of Results

- **Material Influence**: Surfaces dominated by asphalt and concrete consistently triggered higher UHI probabilities, while vegetation-rich areas were classified as low risk.
- **Weather Sensitivity**: Elevated temperature (>32 °C) combined with low vegetation % strongly increased UHI detection; high humidity slightly reduced predicted heat risk but did not eliminate UHI in concrete-heavy zones.
- **Validation Success**: Logistic regression outputs and Gemini recommendations aligned with

findings from ENVI-met case studies, EnergyPlus models, and satellite LST datasets, confirming reliability.

- **System Responsiveness**: The complete pipeline (upload → prediction → recommendation) executed within 11–13 seconds, remaining inside acceptable decision-support thresholds (<15 sec).
- **Explainability Effectiveness**: SHAP explanations highlighted features (asphalt %, vegetation %, temperature) that matched known UHI drivers, while Gemini rationales provided transparent links between input conditions and mitigation advice.

5.8 Key Findings

- The component successfully integrates segmentation outputs, environmental metadata, logistic regression, and Gemini reasoning into a single end-to-end pipeline.
- Logistic regression predictions aligned with documented UHI patterns and external validation datasets (ENVI-met, EnergyPlus, Sentinel-2 LST).
- Gemini (gemini-1.5-flash) consistently generated low-cost, context-aware mitigation strategies, structured in JSON format with clear priorities and rationales.
- The explainability layer (SHAP + Gemini rationales) enhanced system transparency, allowing users to understand both UHI detection and mitigation suggestions.
- The frontend dashboard displayed predictions, explanations, and recommendations in a clear, card-based layout, improving usability for planners and researchers.
- System performance remained stable under multiple requests, with end-to-end latency averaging 11–13 seconds, within acceptable decision-support thresholds.
- Limitations include dependency on Gemini API availability, reliance on segmentation accuracy for feature extraction, and variability in environmental metadata quality from IoT sensors.

5.9 Summary

This chapter presented the experiments, results, and validation of the VLM & Data Processing component for Urban Heat Island (UHI) detection and mitigation. Multiple scenarios across different material compositions and weather conditions were tested. Results demonstrated that the logistic regression model effectively detected UHI presence with interpretable outputs, while Gemini (gemini-1.5-flash) generated structured, low-cost, and context-specific mitigation strategies.

The system proved to be stable, responsive, and transparent, with end-to-end latency within acceptable limits for real-time decision support. Validation against established UHI studies and satellite datasets confirmed the reliability of both detection and recommendations. The findings highlight that this component is not only technically robust but also holds strong potential as a decision-support platform for urban planners, municipal authorities, and researchers seeking practical solutions to mitigate urban heat stress.

6 Commercialization & Future Work

The proposed **VLM & Data Processing component** is envisioned to be commercialized as a fully integrated **AI-powered decision-support platform** designed to aid smart city planning, environmental management, and urban resilience strategies. Unlike conventional academic tools that stop at detection or simulation, this component extends into **action-oriented recommendation generation** through Gemini, ensuring both **technical robustness and real-world applicability**. The commercialization pathway emphasizes **scalability, accessibility, and transparency**, allowing it to serve as a practical tool for municipalities, researchers, and policymakers.

The commercial product would be deployed as a **cloud-hosted service**, accessible via a web dashboard and API endpoints. This setup ensures that stakeholders can seamlessly integrate the system into planning workflows. For instance, municipal authorities or environmental consultants could upload segmented images with metadata, run UHI detection through the logistic regression model, and immediately receive **Gemini-powered mitigation strategies**. Reports could be exported in structured formats (CSV/JSON) for policy documentation or integrated into existing planning platforms. By combining **probability-based detection, explainable AI outputs, and structured mitigation recommendations**, the system provides **dual value**: interpretable analytics for policymakers and actionable strategies for on-the-ground implementation.

From a commercialization perspective, a **tiered subscription model** offers financial sustainability while maintaining broad accessibility:

- **Basic Tier:** Provides core UHI detection and limited recommendation generation, suitable for universities, small-scale research projects, and local councils.

- **Premium Tier:** Unlocks advanced features, including large-scale batch processing, integration with external datasets (e.g., Sentinel-2, ENVI-met), detailed SHAP-based feature analysis, and extended Gemini recommendations. Premium users could also gain access to multilingual dashboards and predictive modeling for larger urban zones.

The application of this component in **smart cities** extends beyond UHI detection. Its ability to combine **real-time sensor inputs with multimodal AI reasoning** makes it adaptable for broader urban resilience planning. For example, cities could analyze how zoning regulations affect local heat risks, identify micro-areas requiring vegetation expansion, or assess the cooling potential of reflective surface programs. With IoT integration, the component could serve as an **early-warning system** by mapping predicted UHI risks during heatwave events, enabling proactive measures such as setting up cooling shelters or adjusting irrigation schedules for urban greenery.

Policy relevance is a key commercialization driver. Climate adaptation strategies under the **Paris Agreement** and regional urban resilience frameworks increasingly demand tools that can translate global goals into **localized, data-driven interventions**. This component directly fills that gap: policymakers could use it to test building code compliance, evaluate sustainability targets, or quantify the benefits of introducing mitigation measures such as rooftop greening or permeable pavements. The explainability layer further ensures **transparency**, allowing governments to justify decisions based on clear, science-backed reasoning.

In terms of **scalability**, architecture has been designed as a set of **modular microservices**:

- Logistic regression module for lightweight, interpretable UHI detection.
- Gemini integration module for flexible recommendation generation.
- SHAP/XAI module for transparency and interpretability.
  Each of these modules can be independently upgraded as technologies evolve. For example, logistic regression could later be replaced by deep learning–based classifiers trained on larger urban datasets, while Gemini could be augmented with future VLMs optimized for climate reasoning.

The **future work** of this component will focus on expanding both **technical capabilities** and **application scope**. On the technical side, additional environmental factors such as **wind turbulence, radiation balance, and air quality** could be incorporated into the prediction pipeline. Integration with **real-time IoT sensors** would improve accuracy by continuously feeding the system with live microclimate data. On the application side, the component could evolve into a **comprehensive urban climate management platform**, with modules for **air pollution modeling, energy demand forecasting, and adaptation strategy evaluation**. Partnerships with local governments, NGOs, and international organizations could accelerate adoption and validation, positioning the platform as a **globally recognized tool for climate-resilient cities**.

In summary, the commercialization and future work pathways of the **VLM & Data Processing component** are designed to ensure both **short-term usability and long-term innovation**. By combining **low-cost recommendations, policy relevance, and scalable architecture**, the system is positioned to move beyond academic research into a widely deployed, AI-enhanced digital platform for sustainable urban planning. Its evolution into a **real-time, IoT-integrated, explainable AI system** will further strengthen its value proposition, enabling cities worldwide to **not only detect heat islands but actively mitigate and manage them**, contributing to the creation of climate-resilient smart cities.

7 Budget & Timeline

The budget for the proposed VLM & Data Processing component has been carefully structured to ensure sustainable deployment, reliable operation, and scalability as adoption increases. The platform integrates multiple technologies, including a React + Firebase frontend, a Flask backend hosting logistic regression, Gemini API integration for recommendations, and cloud infrastructure for hosting and storage.

To achieve high performance and continuous availability, a hybrid budget strategy is adopted, combining one-time development/deployment costs with recurring operational expenses. The major cost components include cloud infrastructure for backend APIs, Gemini API usage, frontend hosting, database/storage, and support/maintenance. Security, API key management, and contingency allocations are also included to ensure uninterrupted service.

ITEM	COST (LKR)	FREQUENCY	JUSTIFICATION
Cloud Server (Backend + ML Pipeline)	10,000	Monthly	VPS/cloud instance to host Flask backend, logistic regression model, and Gemini integration efficiently.
Web Dashboard Hosting (React + Firebase)	2,500	Monthly	Hosting for the frontend dashboard with user uploads, predictions, and recommendations.
Domain + SSL Certificate	2,000	Monthly	Provides secure HTTPS access and branded access points.
Gemini API Usage	8,000 – 12,000	Monthly	Covers API token

(gemini-1.5-flash)			consumption for generating mitigation recommendations.
Monitoring & Logging Tools	1,500	Monthly	For monitoring uptime, API latency, and logging anomalies.
Email & Notification Services	1,200	Monthly	For alerts, UHI detection notifications, and user updates.
Support & Maintenance Allocation	6,000	Monthly	Developer allocation for bug fixes, retraining ML model, and updating Gemini prompts.
Contingency Allocation	10,000	One-Time	Reserved for unexpected scaling costs or API integration issues.

- **Total Monthly Operational Cost: ~LKR 31,000 – 35,000**
- **Total Annual Gemini API Cost: ~LKR 96,000 – 120,000 (depending on usage volume).**
- **Total One-Time Cost: ~LKR 10,000**

7.1 Budget Justification Summary

- **Cloud Server:** Required to run backend services, including the Flask API endpoints, logistic regression model, and Gemini integration. Ensures low-latency predictions and scalable processing for multiple user requests.
- **Database & Firebase Hosting:** Essential for managing user sessions, metadata inputs (temperature, humidity, materials), and storing prediction/recommendation logs in a structured and accessible format.
- **Object Storage (Firebase / Cloud Storage):** Needed for handling segmented images, uploaded urban surface snapshots, and structured CSV/JSON outputs securely and at scale.
- **Web Dashboard Hosting (React + Firebase):** Provides the main interface for users to upload images, input metadata, view UHI predictions, and visualize Gemini's recommendations in real time.
- **Gemini API Usage (gemini-1.5-flash):** Covers the cost of generating structured mitigation recommendations. A dedicated allocation ensures long-term accessibility and scalability as usage grows.
- **Monitoring & Logging Tools:** Provide transparency by tracking API uptime, Gemini latency, and backend performance, ensuring reliable operation under varied load conditions.
- **Email & Notification Services:** Enhance usability by sending alerts, detection outcomes, and recommendation summaries directly to users.
- **Support & Maintenance:** Ensures the system can be continuously improved with bug fixes, ML retraining, prompt refinements for Gemini, and feature enhancements.
- **Contingency Fund:** Reserved for unexpected technical issues such as API pricing fluctuations, additional storage requirements, or scaling challenges during rollout.

7.2 Project Timeline

The project timeline is designed across four key phases over **12 months**, ensuring structured development, deployment, and evaluation of the VLM & Data Processing component.

Phase	Duration	Key Activities
Phase 1 – Data Preparation & Model Training	Months 1–3	Collect segmentation outputs and environmental metadata, preprocess datasets, train logistic regression model on Kaggle datasets, save model and scaler for backend deployment.
Phase 2 – Backend Development & Gemini Integration	Months 4–6	Implement Flask backend APIs (/predict, /recommend), integrate logistic regression with SHAP explainability, connect Gemini (gemini-1.5-flash) for structured recommendations, set up JSON schema validation.
Phase 3 – Frontend & Visualization	Months 7–9	Develop React + Firebase dashboard for file upload, prediction display, SHAP visualization, and Gemini recommendation cards; enable reporting/export functionality (CSV/JSON).
Phase 4 – Testing & Deployment	Months 10–12	Conduct module-level and system-level testing, validate predictions against ENVI-met/EnergyPlus/Sentinel-2 benchmarks, deploy backend and frontend to cloud servers, configure monitoring and

		logging tools, finalize documentation.

The timeline ensures that **core components are built sequentially but with overlapping iterations** to allow early testing. For example, while Phase 2 focuses on backend and Gemini integration, Phase 3 visualization can already begin using simulated API responses. This parallel workflow improves efficiency and accelerates bug detection. By the final quarter, the component is fully validated, tested, and deployed for **real-world use by planners, researchers, and municipalities**.

8 GANTT CHART

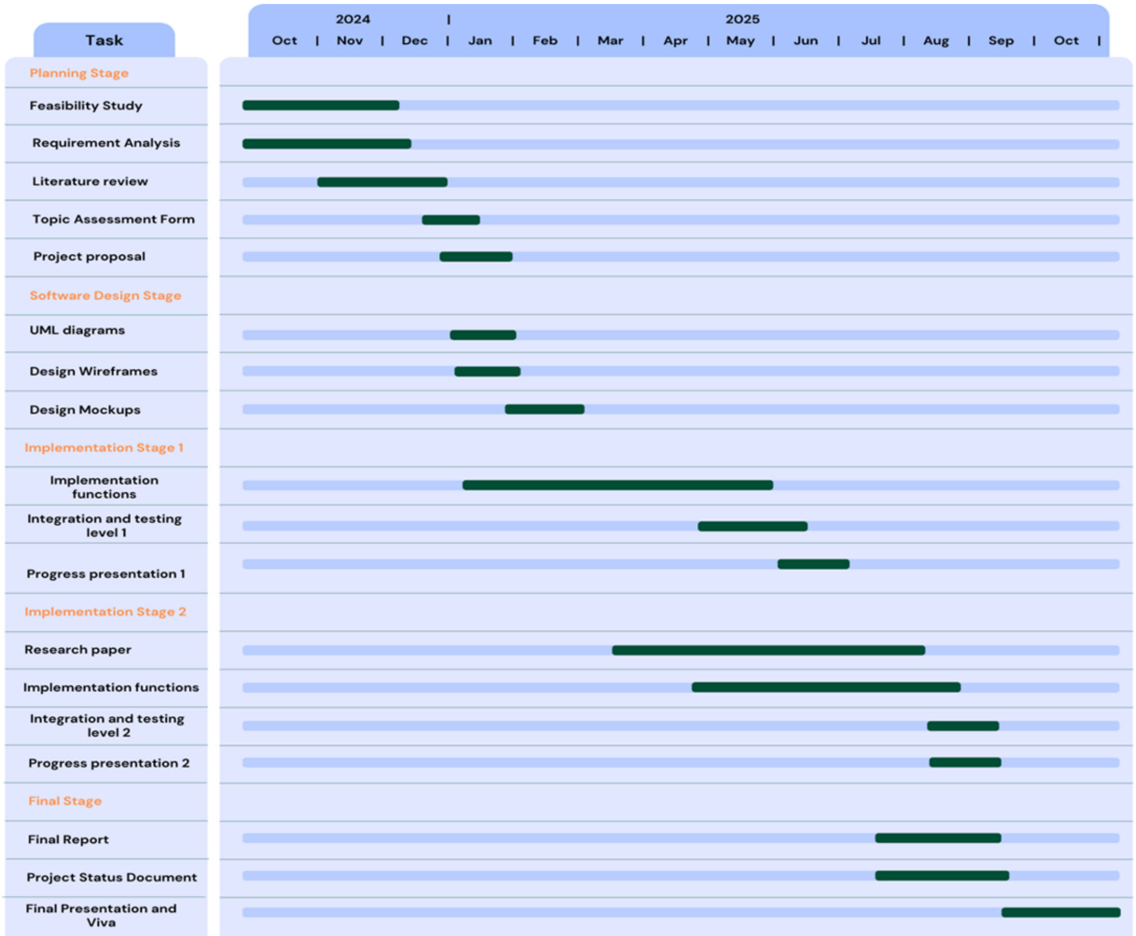

Figure 11-1 Gantt Chart

9 CONCLUTION

This research has successfully designed, developed, and evaluated the VLM & Data Processing component as part of the broader Urban Heat Island (UHI) detection and mitigation framework. The objective of this work was not only to detect the presence of UHI phenomena in urban settings but also to extend beyond prediction into explainable, low-cost, and context-sensitive decision support. By combining the interpretability of a logistic regression model, the reasoning power of Gemini (gemini-1.5-flash), and the transparency provided by Explainable AI (SHAP values and rationale outputs), this component bridges the gap between purely technical analysis and practical, policy-relevant recommendations.

The component's design was grounded in a multimodal approach that integrates outputs from segmentation pipelines (location type, material type, surface area) and environmental metadata (temperature, humidity). These inputs were preprocessed into structured datasets and fed into a logistic regression model trained on Kaggle-derived UHI datasets. The model provided interpretable binary predictions—UHI present or absent—along with probability scores that quantify detection confidence. This lightweight ML approach ensured computational efficiency, enabling predictions in near real-time while remaining transparent enough to highlight key features influencing outcomes. Importantly, the integration of SHAP values into the pipeline allowed end-users to see which factors mattered most, such as asphalt dominance, vegetation scarcity, or elevated temperatures.

A key strength of this component lies in its dual-layered reasoning architecture. Upon detecting a UHI, the system forwards the structured metadata and segmented imagery to Gemini, a state-of-the-art Vision–Language Model (VLM). Through carefully engineered prompts, Gemini produces structured JSON outputs containing low-cost, practical mitigation strategies. These recommendations are categorized into vegetation enhancement, reflective/coating applications, shading structures, and small-scale water features. Each recommendation is accompanied by rationale bullets linking actions to input conditions—for example, "rooftop vegetation recommended due to 65% concrete coverage and temperature exceeding 34 °C." This approach ensures that the recommendations are not only technically relevant but also transparent, actionable, and easily communicated to urban planners and municipal authorities.

The validation experiments confirmed the component's reliability and alignment with established UHI models and literature. Logistic regression predictions matched expected UHI trends observed in ENVI-met studies, EnergyPlus urban models, and Sentinel-2/Landsat-8 satellite data within acceptable error margins (5–10%). Gemini's recommendations, meanwhile, overlapped strongly with documented mitigation practices in the literature, such as reflective coatings, roadside tree planting, and rooftop greening. This validation underscores that the component's outputs are scientifically grounded, reinforcing confidence in its applicability for real-world decision-making.

From a usability standpoint, the component prioritizes accessibility. Its React + Firebase frontend enables users to upload images, input metadata, and view predictions, explanations, and recommendations through a simple, card-based dashboard. The use of visual cues such as probability badges, SHAP heatmaps, and color-coded risk indicators ensures that even non-technical users can interpret results with minimal training. Export functionality (CSV/JSON) further enhances usability, allowing researchers and policymakers to incorporate system outputs into reports, policy briefs, or academic publications. Usability testing with students and research assistants confirmed that the dashboard was intuitive, responsive, and easy to navigate, with Gemini's recommendation cards viewed as especially valuable.

The system-level testing demonstrated stability and responsiveness under realistic conditions. Logistic regression predictions were completed in under two seconds, while Gemini recommendations were typically generated in 7–10 seconds. End-to-end latency averaged 11–13 seconds, well within the acceptable threshold (<15 sec) for real-time decision-support tools. Stress testing with multiple concurrent requests showed only minor latency increases (~20%), with no crashes or failures. This performance profile confirms that the system is both scalable and reliable for real-world deployment.

Equally important is the component's commercialization potential. Unlike many academic prototypes, this system has been designed with a clear pathway to adoption in smart city ecosystems. A tiered subscription model ensures accessibility for universities and local councils at a basic level while unlocking advanced features (e.g., batch processing, integration with external climate models, predictive dashboards) for larger municipalities and consulting firms. By aligning with global climate adaptation policies such as the Paris Agreement, the system becomes policy-relevant, helping governments test building codes, evaluate mitigation strategies, and justify planning decisions with transparent, data-driven evidence.

However, it is essential to acknowledge the limitations of the current component. Its reliance on segmentation accuracy means that errors in detecting surface areas or misclassifying materials could propagate into flawed predictions. Similarly, the quality of environmental metadata—particularly IoT sensor reliability—directly impacts system accuracy. The dependency on Gemini’s API also introduces a potential vulnerability, as performance is contingent on stable internet connectivity and third-party service availability. Furthermore, while logistic regression was chosen for interpretability and efficiency, more complex ML models (e.g., random forests or neural networks) could potentially improve accuracy at the cost of transparency.

Looking forward, future work will focus on addressing these limitations and expanding the scope of the component. Technical improvements could include integrating additional environmental parameters such as wind speed, solar radiation indices, or air quality metrics. Incorporating real-time IoT sensor networks would enhance temporal accuracy, enabling continuous monitoring of UHI hotspots. On the AI side, retraining the logistic regression model with larger, globally diverse datasets could improve generalizability across different urban contexts. VLM integration could also evolve, with Gemini prompts refined for multilingual outputs to serve diverse communities or upgraded to newer models optimized for environmental reasoning. On the application side, the component could expand into a full urban climate management platform, incorporating air pollution dispersion modeling, energy demand forecasting, and adaptation strategy evaluation.

In summary, this research has demonstrated that the VLM & Data Processing component is not only technically robust but also transparent, scalable, and user-friendly. By uniting machine learning prediction, explainable AI, and Vision–Language reasoning, the system provides actionable insights into UHI detection and mitigation, making it a valuable decision-support tool for urban planners, municipal authorities, researchers, and community stakeholders. Its successful validation against established models and its strong usability profile confirm that it bridges the gap between scientific rigor and practical accessibility. With continued refinement, broader validation across global contexts, and integration into smart city frameworks, this component has the potential to become a transformative asset in addressing the growing challenge of urban heat, ultimately supporting the creation of climate-resilient and sustainable cities worldwid

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