AI-Driven Detection and Mitigation of Urban Heat Island Effects Using Vision-Language Models

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August 2025

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Dissertation submitted in partial fulfillment of the requirements for the Bachelor of Science (Hons) in Information Technology Specialized in Software Engineering

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DECLARATION

We hereby declare that this dissertation is our own work and does not incorporate, without acknowledgement, any material previously submitted for a Degree or Diploma in any other University or Institute of Higher Learning. To the best of our knowledge and belief, it does not contain any material previously published or written by another person, except where acknowledgement is made in the text.
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Abstract

Urban Heat Islands (UHIs) are a critical environmental challenge driven by rapid urbanization, leading to elevated local temperatures, increased energy demand, and negative impacts on public health and sustainability. This research presents an integrated framework for the **AI-driven detection and mitigation of UHI effects**, combining computer vision, Internet of Things (IoT) sensing, server-side intelligence, and digital twin simulations.

The system is composed of four interdependent modules. First, an **image analysis pipeline** applies deep learning models to perform object detection, semantic segmentation, material classification, and surface area estimation from single 2D urban images. Second, a **mobile IoT sensing device**, built on ESP32 with GPS, IMU, and a thermal sensor, performs depth-aware localization and real-time temperature validation using visual feature matching. Third, a **server-side intelligence layer** integrates field data with pre-analyzed image metadata, employing machine learning for UHI detection and a Vision–Language Model (VLM) for generating context-specific mitigation strategies. Finally, a **simulation tool** constructs 3D digital twins using GIS and Blender, incorporates weather APIs and solar exposure modeling, and applies MATLAB Simscape for physics-based heat transfer modeling, with visualization enabled via a React + Three.js interface.

Experimental evaluations demonstrated accurate segmentation of urban features, reliable navigation and thermal measurements in dynamic environments, and high interpretability of recommendations through Explainable AI techniques. Validation against established tools such as ENVI-met and EnergyPlus confirmed the credibility of simulation outputs, while VLM-based reasoning provided practical, low-cost strategies such as increased vegetation cover, reflective materials, and water-based cooling systems.

By integrating multimodal AI, IoT sensing, and digital twin simulations, this research delivers a **scalable, cost-effective, and interpretable framework** for UHI monitoring and mitigation. The findings support smart city development, provide actionable insights for urban planners, and contribute to sustainable and climate-resilient urban design.

Keywords: Urban Heat Island, Vision–Language Model, IoT Sensing, Image Segmentation, Digital Twin, Sustainable Urban Planning

Acknowledgement

First and foremost, we would like to express our sincere gratitude to our supervisor, Mr. Vishan Jayasinghearachchi, for his invaluable guidance, encouragement, and expertise throughout the course of this research. His constructive feedback and continuous support greatly contributed to the successful completion of this project.

We are also deeply grateful to our co-supervisor, Ms. Kaushalya Rajapakse, for her continuous mentorship and advice, which helped refine our research direction and improve the quality of this work. In addition, we extend our appreciation to our external supervisor, Dr. Rajitha de Silva of the University of Lincoln, for his expert insights, technical advice, and critical suggestions that strengthened both the methodology and outcomes of our study.

Our thanks also go to the Department of Software Engineering, Sri Lanka Institute of Information Technology (SLIIT), for providing the academic environment, resources, and support necessary for carrying out this research.

We would also like to acknowledge our project team members for their collaboration, commitment, and contributions across all stages of the project. The success of this work is a result of collective effort, knowledge sharing, and mutual support.

Finally, we extend our heartfelt gratitude to our families, friends, and colleagues for their patience, encouragement, and moral support throughout this journey. Their unwavering belief in us provided the strength to overcome challenges and remain dedicated to completing this work successfully.

This dissertation stands as a testament to the combined efforts, mentorship, and inspiration provided by all those who supported us, and we remain sincerely thankful for their contributions.

Contents

List of Figures

List of Tables

List of Abbreviations

Abbreviation	Description
UHI	Urban Heat Island
IoT	Internet of Things
GNSS	Global Navigation Satellite System
GPS	Global Positioning System
IMU	Inertial Measurement Unit
ROI	Region of Interest
LST	Land Surface Temperature
RTK	Real-Time Kinematic (GNSS)
PPP	Precise Point Positioning
EKF	Extended Kalman Filter
SLAM	Simultaneous Localization and Mapping
RANSAC	Random Sample Consensus
MAE	Mean Absolute Error
RMSE	Root Mean Square Error
IQR	Interquartile Range
RTT	Round-Trip Time
PLR	Packet Loss Rate
CDF	Cumulative Distribution Function
GCP	Ground Control Point
HDOP	Horizontal Dilution of Precision
UUID	Universally Unique Identifier
MQTT	Message Queuing Telemetry Transport
MQTT-SN	MQTT for Sensor Networks
CoAP	Constrained Application Protocol
CNN	Convolutional Neural Network
VLM	Vision-Language Model
QUIC	Quick UDP Internet Connections

Introduction

Urban areas worldwide are experiencing unprecedented growth, with over 68% of the global population projected to reside in cities by 2050[1]. This rapid urbanization has intensified the urban heat island (UHI) effect, a phenomenon where urban areas become significantly warmer than their rural counterparts[2]. The UHI effect is a pressing concern with wide-ranging implications for public health, energy consumption, and environmental sustainability[3]. Elevated urban temperatures exacerbate heat stress, increase electricity demand for cooling, and contribute to air pollution, placing additional burdens on urban infrastructures[4]. The fundamental drivers of UHI formation are well-established: reduced vegetation cover, increased impervious surfaces like concrete and asphalt that absorb and retain heat, anthropogenic heat emissions, and altered wind patterns[5]. These factors can create temperature differences of $1 - 10°C$ between urban cores and surrounding rural areas, with some extreme cases showing differences up to $12°C$[6].

Figure 1.1 illustrates the UHI effect, showing the temperature variations across rural, suburban, and urban areas and highlighting the temperature differentials that arise due to urbanization. This visual representation underscores the magnitude and spatial distribution of heat accumulation in densely built environments.

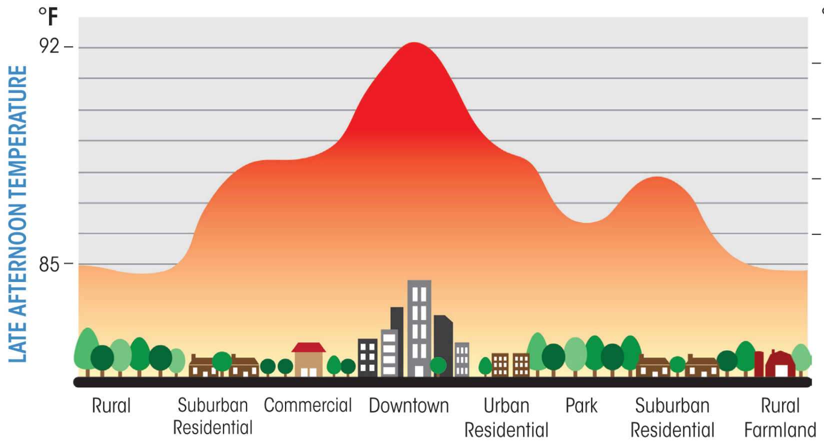


Figure 1.1: Illustration of the Urban Heat Island (UHI) effect, showing temperature variations between rural, suburban, and urban areas with specific temperature differentials.

The significance of this issue has motivated the development of a comprehensive research system that integrates multiple components to address the UHI effect. The workflow begins with the capture of images enriched with GPS and gyroscopic data via a mobile application. These images are then processed by the image analysis component, which employs advanced object detection and segmentation techniques. This stage utilizes YOLOv8 for object localization and MobileSAM for pixel-level segmentation, enabling precise identification of urban features.

The segmented images are subsequently transmitted to the IoT component, which focuses on real-time thermal validation. This system autonomously navigates to target coordinates to collect thermal measurements, bridging the gap between visual analysis and physical sensing. The integration of these two components ensures a robust and accurate dataset for further analysis.

The results from the image analysis and IoT components are then utilized by the Vision-Language Model (VLM) framework. This framework combines structured machine learning-based detection with multimodal reasoning to detect the presence of UHIs and propose actionable mitigation strategies. The final component, a simulation tool, integrates Geographic Information System (GIS) data, 3D digital twins, and MATLAB-based simulations to predict UHI effects and evaluate potential interventions. This holistic approach not only identifies UHI hotspots but also provides urban planners with data-driven solutions for mitigation.

By integrating these components, the research system offers a comprehensive, scalable, and actionable framework to address the challenges posed by the UHI effect, paving the way for more sustainable urban development.

1.1 Background Literature

Research on Urban Heat Islands (UHIs) has evolved significantly, driven by the need for effective solutions to climate resilience, urban sustainability, and public health challenges[7]. Early research primarily relied on remote sensing techniques and field measurements[8]. Satellite imagery from platforms such as Landsat, MODIS, and Sentinel-2 has enabled high-resolution monitoring of land surface temperature (LST) and vegetation cover at city-wide and regional scales[9, 10]. While these methods are valuable for identifying macro-level UHI patterns, they often lack the granularity for micro-level analysis and are limited by coarse spatial and temporal resolution, cloud interference, and indirect correlation with human thermal comfort[11, 12]. To address this, fixed meteorological stations offer high-accuracy measurements but are expensive and provide limited spatial coverage, making city-wide deployment infeasible[12, 13].

To overcome the limitations of traditional methods, researchers have increasingly turned to computational and AI-based approaches. Simulation tools like ENVI-met and EnergyPlus model physical processes such as shading and evapotranspiration to inform climate-resilient design[9, 10]. However, these systems are often computationally intensive, requiring significant expertise and resources, which limits their scalability for real-time applications[12, 13].

The integration of Geographic Information System (GIS) data, 3D modeling, and MATLAB-based thermal simulations has emerged as a promising approach for UHI analysis. By embedding environmental metadata such as material properties, wind speed, and sun exposure into digital twins, researchers can simulate heat transfer and temperature distribution across urban structures[14]. This method enables the prediction of UHI effects at both building and city-block scales, offering valuable insights for urban planners[15].

Advancements in object detection and segmentation have further enhanced urban scene analysis. Techniques such as YOLOv8 for object localization and MobileSAM for pixel-level segmentation enable precise identification of urban features[16, 17]. These methods are complemented by material classification engines like CLIP, which align images with text descriptions for semantic identification[18]. Depth estimation models based on Vision Transformers, such as DepthPro, facilitate the generation of metrically accurate 3D meshes from monocular images, addressing challenges like scale ambiguity[12].

The application of Vision-Language Models (VLMs) has introduced a new dimension to UHI research. By combining structured predictive modeling with multimodal reasoning, VLMs like Gemini analyze segmented urban imagery and metadata to generate actionable mitigation strategies[19]. These frameworks incorporate Explainable AI (XAI) techniques to justify both detection results and recommended interventions, enhancing transparency and decision-making for urban planners[9, 10].

These collective advancements highlight the potential of integrated, AI-driven frameworks to address the challenges posed by UHIs. By leveraging diverse technologies, researchers aim to bridge the gap between passive detection and active, data-driven mitigation strategies, paving the way for more sustainable urban development.

1.2 Research Gap

Despite significant progress in UHI research, several critical gaps remain, particularly in the integration of diverse technologies to create comprehensive, actionable, and user-friendly systems.

1.2.1 Fragmentation and Disconnect

A persistent limitation is the fragmentation of methodologies and tools[1, 2]. Remote sensing and GIS are effective for large-scale temperature detection but lack the resolution to capture fine-grained variations at the building level[3]. Conversely, while thermal sensing platforms provide accurate temperature measurements, they often lack contextual understanding of the surrounding urban features, creating a disconnect between visual identification and thermal validation[4, 5]. Similarly, existing UHI detection tools often stop at prediction, failing to generate actionable, low-cost recommendations for urban planners[6, 20, 21].

1.2.2 Metadata and Dynamic Analysis

Most current digital twins and 3D models represent only geometry and textures, failing to embed critical physical and material properties necessary for accurate thermal analysis[14, 15]. Without metadata such as thermal conductivity, specific heat capacity, and mass, simulations rely on generic assumptions, which reduces accuracy[22, 19]. Furthermore, many UHI models operate under static assumptions, failing to dynamically adapt to changing environmental conditions like wind, humidity, and solar radiation using real-time data from APIs[16, 17].

1.2.3 Decision-Making Support Gap

Simulation results are often too technical or abstract for urban planners to translate into practical policy, creating a lack of decision-making support for non-expert users[1, 2]. While advanced ML models can achieve high predictive accuracy, they often function as "black boxes" with limited transparency, reducing trust and limiting real-world adoption[3, 4, 5]. There is a critical need for frameworks that provide not only predictions but also justifications for why certain interventions are recommended, a core principle of Explainable AI (XAI)[9, 10].

1.2.4 Resource and Cost Barriers

Advanced UHI assessment services are costly and often inaccessible to smaller municipalities or developing urban regions[20, 21]. The high capital expenditure for monitoring systems exacerbates environmental inequities[6, 2]. Moreover, surface area estimation from monocular images is hindered by scale ambiguity, and existing methods often require expensive multi-view systems or manual calibration, which are impractical for single-image scenarios[22, 19].

1.2.5 Integration Challenges

Tools and technologies used in UHI research are often not interoperable, hindering comprehensive analysis. This lack of integration between tools limits the ability to create unified frameworks for addressing UHI challenges holistically.

1.2.6 Dynamic Environmental Adaptation

Most studies focus on static analysis, neglecting dynamic environmental changes. Incorporating real-time data streams for wind, humidity, and solar radiation remains an underexplored area.

1.2.7 Metadata Utilization

Metadata, which could enhance model accuracy and insights, is underutilized in current systems. Embedding metadata such as thermal conductivity and specific heat capacity into models can significantly improve simulation accuracy.

1.3 Research Problem

The comprehensive analysis of urban environments for UHI effects from diverse data sources presents significant challenges that existing solutions fail to address holistically. This research aims to address the following key problems:

- **How can an integrated digital twin simulation tool be developed to combine GIS datasets, 3D modeling, environmental data, and MATLAB-based physics simulations to predict and analyze the Urban Heat Island effect?** Current approaches lack a single framework that integrates GIS, real-time weather data, 3D urban models, and simulation engines, leading to fragmented and incomplete analyses[1, 2]. This problem is compounded by a limited focus on building components and the static nature of many existing tools[3, 4].

- **How can a mobile IoT sensing platform equipped with autonomous navigation and thermal sensing capabilities provide accurate, validated temperature measurements of urban objects identified through image analysis while maintaining cost-effectiveness and scalability?** This addresses the limitations of existing mobile sensing approaches, which often lack autonomous navigation, precise alignment with measurement targets, and robust mechanisms to verify that thermal readings correspond to the intended objects[20, 21].

- **How can an integrated framework combine structured machine learning-based detection with Vision-Language Model (VLM)-based multimodal rea-**

soning to provide transparent, low-cost, and context-specific mitigation strategies for Urban Heat Islands? This addresses the gap where most UHI prediction systems, while accurate, fail to offer actionable decision-support and operate as "black boxes" with limited explainability[3, 4, 5].

- **How can a unified computational pipeline overcome the limitations of coarse object detection, material heterogeneity, and scale ambiguity to comprehensively analyze architectural structures from a single 2D image?** The challenge here is to create a single system that provides precise object delineation, granular material identification, and metrically accurate surface area estimation, all of which are critical for applications in urban planning and design[22, 19].

- **How can dynamic environmental adaptation be incorporated into UHI models?** Existing models often fail to account for real-time changes in environmental conditions such as wind, humidity, and solar radiation, limiting their applicability in dynamic urban settings.

- **How can IoT platforms enhance the localization and measurement of segmented urban objects?** The integration of depth-aware object localization and thermal sensing remains a challenge for scalable and cost-effective urban heat monitoring.

These research problems collectively highlight a need for multi-modal, integrated, and explainable frameworks that bridge the gap between passive UHI detection and active, data-driven mitigation strategies.

1.4 Research Objectives

The overarching goal of this research is to develop and validate a comprehensive, integrated, and intelligent framework for Urban Heat Island (UHI) detection and mitigation. To achieve this, the following main and specific objectives have been defined:

1.4.1 Main Objective

To design and implement an integrated simulation and sensing framework that combines GIS data, AI-driven image analysis, IoT sensing, and physics-based thermal modeling to accurately detect, simulate, and provide actionable, context-aware mitigation strategies for Urban Heat Islands at both the building and neighborhood scales.

1.4.2 Specific Objectives

1. Simulation and Modeling:

- To design a **metadata-enriched 3D building model framework** that embeds critical thermal parameters (e.g., thermal conductivity, specific heat capacity) into digital twins to enable accurate thermal simulations[9, 10].
- To integrate **GIS and remote sensing data** to provide a holistic spatial context for building-level simulations, using datasets like GIS layers and Sentinel-2/Landsat-8 imagery[1, 2].
- To incorporate **real-time weather data inputs** from APIs and **sunlight exposure calculations** using SunCalc into the simulation pipeline to enable dynamic and adaptive modeling that reflects current conditions[3, 4].
- To simulate thermal behavior using **MATLAB Simscape Thermal** to model heat transfer processes for individual building components and predict temperature distributions[5, 21].

2. Sensing and Data Processing:

- To implement an **autonomous navigation and object alignment system** for a mobile IoT platform that uses GPS coordinates, IMU-based heading data, and feature-matching algorithms to precisely reach and align with target objects[20, 21].

- To develop a robust methodology to accurately map real-time temperature readings from a thermal sensor onto corresponding geographic objects identified through image segmentation[21, 5].
- To implement an end-to-end computational pipeline that integrates **object detection (YOLOv8)**, **pixel-level segmentation (MobileSAM)**, **material classification (CLIP)**, and **surface area estimation** to extract detailed, quantitative insights from a single 2D image[16, 17, 18, 12].

3. AI-Driven Decision Support:

- To develop a **logistic regression model** to predict the presence of UHIs using structured environmental data in a transparent and interpretable manner[1, 2].
- To leverage a **Vision-Language Model (Gemini)** to process both segmented urban images and structured metadata to generate low-cost, practical, and scalable mitigation strategies (e.g., reflective coatings, urban greening)[3, 4, 5].
- To incorporate **Explainable AI (XAI)** mechanisms that provide clear reasoning for both UHI detection results and the generated mitigation recommendations, thereby enhancing trust and adoption among urban planners[9, 10].

4. Validation and Usability:

- To develop a **visualization and decision-support interface** (e.g., using React and Three.js) that translates complex simulation outputs and AI recommendations into formats understandable by non-technical users[21, 5].
- To validate the integrated tool against documented UHI patterns and existing models to ensure its credibility and reliability for real-world applications[6, 20].

Methodology

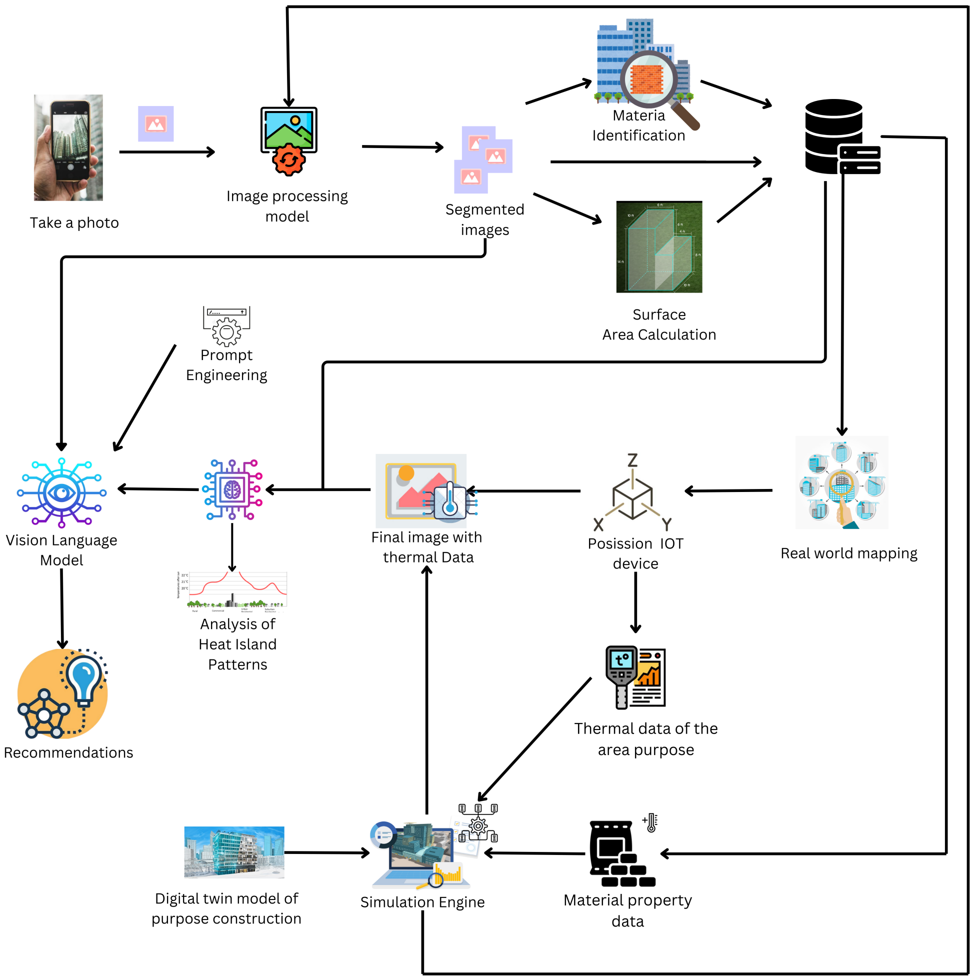


Figure 2.1: full system overview

The methodology architected for this research represents a paradigm shift in the approach to urban environmental analysis, moving beyond conventional, siloed studies to propose a comprehensive and deeply integrated framework for the complex challenge of Urban Heat Island (UHI) detection and mitigation. Traditional approaches have often been constrained by their reliance on isolated datasets—such as satellite thermal imagery alone or sparse, fixed sensor networks—or by singular modeling techniques that provide a snapshot in time but lack the dynamism for predictive scenario planning. These limitations fracture the analytical process, creating gaps between data collection, interpretation, and actionable insight.

In stark contrast, this project is founded on the principle of synergistic integration, weaving together four advanced technological strands into a single, cohesive analytical fabric. It connects the microscopic detail of computer vision, which deciphers the urban fabric material-by-material, with the macroscopic validation of a mobile IoT-based sensing platform that grounds truth in physical reality. This robust data foundation is then fused within a powerful, cloud-based data integration and intelligence layer, which not only unifies the information but also applies artificial intelligence to generate diagnostic and prescriptive insights. Finally, this entire pipeline feeds a sophisticated digital twin simulation environment, transforming static data into a dynamic, living model of the urban climate capable of forecasting the outcomes of interventions.

This holistic architecture did not emerge fully formed but was rigorously evolved through iterative cycles of design, development, evaluation, and refinement, adhering closely to the principles of design science research. This methodological framework emphasizes the creation of innovative artifacts—in this case, the entire integrated system and its constituent components—and their rigorous validation within a real-world context. Each module, from the image analysis algorithm to the robotic sensor platform, was prototyped, tested in actual urban environments, critiqued, and refined based on empirical performance and practical constraints. This iterative process ensured that the solutions were not merely academically sound but were also robust, usable, and effective when confronted with the messy complexities of the real world.

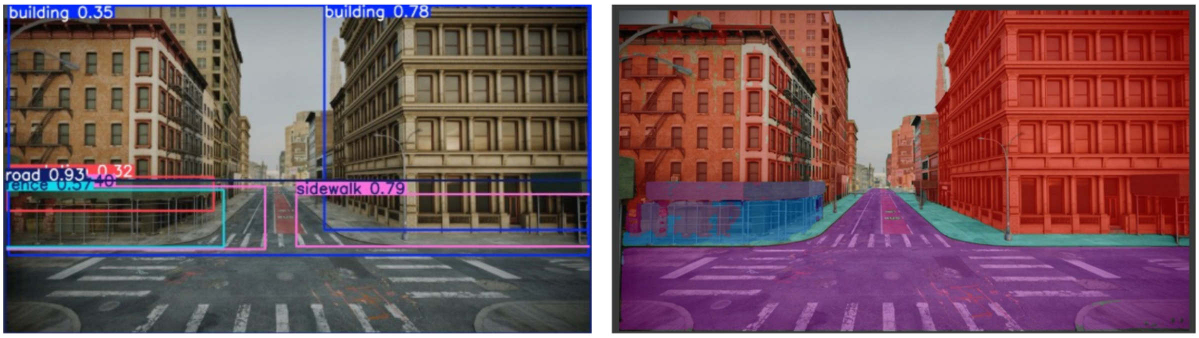
Crucially, each component of the system was engineered with a dual identity: to excel as a standalone tool while being inherently designed for seamless integration with the others. The APIs of the server layer were crafted to anticipate the data needs of the simulation. The output formats of the image analysis module were structured to be directly consumed by the digital twin. The validation data from the IoT robot was formatted to continuously retrain and improve the AI models. This architectural philosophy of interoperability is what enables a true end-to-end solution, a closed-loop system that flows effortlessly from panoramic data acquisition to street-level validation, to intelligent synthesis, and finally to predictive simulation. It is this end-to-end capability that transforms the methodology from a collection of technical exercises into a powerful, scalable, and replicable framework for intelligent urban stewardship, setting a new standard for data-driven climate resilience planning

The research began with a thorough exploration of the urban climate literature, including studies on remote sensing, machine learning, geospatial modeling, and IoT deployment. This exploration highlighted a recurring gap in current UHI research: while satellite imagery provides a broad understanding of surface temperature distribution, it lacks sufficient spatial and temporal granularity to capture street-level thermal dynamics. IoT-based solutions, although capable of fine-grained measurement, are often too expensive or logistically complex to deploy at a city scale. Furthermore, most urban climate simulation tools, such as ENVI-met or EnergyPlus, require expert knowledge to operate and cannot easily incorporate real-time environmental data. These findings underscored the necessity of an integrated methodology, combining the scalability of AI-powered vision models with the accuracy of IoT sensing and the predictive capabilities of simulation engines, presented in an accessible interface for urban planners.

The research approach was structured around four interconnected components, each developed as a subproject but merged through a unified architecture.

2.1 Image Analysis Module

The Image Analysis Module served as the foundational and most critical component of the entire urban analytics system, acting as its synthetic eyes and perceptual brain.



Object Detection Output Segmentation Output

Figure 2.2: object detection and segmentation

Its core mission was to transform raw, multi-sourced visual data—captured from the sweeping vistas of satellites, the mid-altitude perspectives of drones, and the granular detail of street-level imagery—into a structured, quantifiable, and semantically rich model of the urban environment. This transformation was achieved through a sophisticated pipeline that integrated state-of-the-art deep learning models with rigorous data engineering, enabling the extraction of detailed information on material distribution, geometric properties, and thermal parameters for every visible surface.

The journey of this data began with a crucial preprocessing stage, designed to harmonize the disparate inputs into a coherent and reliable dataset. High-resolution imagery from drones and Sentinel-2 satellites underwent orthorectification and precise georeferencing. This process corrected for topographic relief and sensor tilt, ensuring that every pixel was accurately aligned with real-world geographic coordinates, a non-negotiable prerequisite for any subsequent spatial analysis. To combat the inherent challenges of outdoor imagery, such as shadows, glare, and variable atmospheric conditions, contrast enhancement techniques like Contrast Limited Adaptive Histogram Equalization (CLAHE) were employed to standardize lighting and reveal subtle details. Furthermore, data augmentation was strategically used to artificially expand the training dataset, introducing variations in rotation, scale, and brightness. This practice was instrumental in building model robustness, ensuring the system could perform reliably under the unpredictable and diverse conditions of a real-world urban landscape.

At the heart of the module lay a multi-stage deep learning architecture for object detection and segmentation. The system first employed a fine-tuned YOLOv8 model, chosen for its optimal balance between inference speed and accuracy, to perform initial object detection across vast urban scenes. This model acted as a rapid scout, identifying and broadly locating key urban features like buildings, vehicles, roads, and vegetation. However, to move from bounding boxes to precise outlines, the system integrated the Segment Anything Model (SAM). SAM's exceptional capability to refine object boundaries was pivotal for delineating complex and fine-grained structures—such as the intricate edges of building facades, narrow pavements, tree canopies, and building overhangs—with a level of precision that traditional models struggled to achieve. This precise segmentation was the essential first step in isolating individual surfaces for further analysis.

Once segmented, each object was classified according to a comprehensive material taxonomy, including concrete, asphalt, vegetation, metal, glass, and modern features like solar panels. To elevate classification accuracy, particularly for ambiguous or novel surfaces, the system incorporated CLIP, a visionary vision-language model. CLIP allowed the classification pipeline to leverage semantic understanding by evaluating the similarity between visual patches and textual prompts. For instance, engineers could guide the model with descriptive prompts like "weathered concrete with high albedo" or "corrugated metal roofing," enabling it to resolve uncertainties and achieve significantly better generalization beyond its initial training data. This fusion of visual and linguistic intelligence represented a significant leap beyond conventional classification techniques.

A truly novel aspect of this module was its ability to infer three-dimensional properties from two-dimensional imagery. This was accomplished through the integration of monocular depth estimation, specifically using the Depth Anything V2 model. By analyzing visual cues such as texture gradients, occlusion, and perspective, the model could approximate depth maps from single images. This capability was transformative, as it allowed the system to calculate real-world surface areas of buildings (crucial for energy modeling), estimate angles of incidence for solar radiation exposure, and infer the volumetric properties of objects. These derived geometric properties were not merely descriptive; they were fundamental inputs for downstream physics-based simulations, enabling accurate modeling of urban heat islands, solar energy potential, and thermodynamic energy flows. In essence, the Image Analysis Module did not just see the city as a flat picture; it reconstructed a functional, quantified, and dynamic digital twin, forming the indispensable data foundation upon which the entire system was built.

2.2 IoT-based Mobile Sensing Platform

The creation of the Image Analysis Module provided a powerful, AI-driven lens through which to view the urban environment, generating a rich digital representation of its material composition and inferred thermal properties. However, the research team was acutely aware that the predictions of even the most sophisticated deep learning models reside in a probabilistic realm, requiring rigorous, ground-truth validation to transition from a compelling digital twin to a reliable tool for scientific and urban planning applications. This critical need for empirical verification led to the design and deployment of the project's second core component: an innovative IoT-based mobile sensing platform.

This platform was conceived to bridge the gap between the abstract world of pixels and the concrete reality of physical measurement. It materialized as a custom robotic chassis, a nimble ground vehicle engineered for autonomy and precision. At its heart was an ESP32 microcontroller, coordinating a suite of sensors: an MLX90640 thermal array sensor to capture non-contact temperature data, a GPS module for broad geolocation, and an inertial measurement unit (IMU) for precise orientation tracking. Deployed along predefined routes, this robot navigated the urban fabric, its movements orchestrated and its data streamed back to a central server in real-time using the MQTT protocol, a lightweight standard perfectly suited for the low-bandwidth, high-frequency demands of IoT ecosystems.

The platform's true ingenuity, however, lay in its solution to a fundamental challenge of mobile robotics: positional accuracy. Standard GPS coordinates are often insufficient to guarantee that a sensor is pointing at the exact building facade or pavement segment identified by the AI model. To overcome this, the team implemented a sophisticated visual confirmation step before any data logging occurred. Using SuperGlue, a deep learning-based feature-matching algorithm, the robot would compare its own live camera feed against the image segment supplied by the Image Analysis Module. By identifying and aligning key visual features, the robot could autonomously confirm—and minutely adjust its orientation to ensure—that its field of view was perfectly aligned with the AI-predicted target. This innovative fusion of computer vision and robotics effectively mitigated GPS drift and navigation inaccuracies, guaranteeing the fidelity of the measurement by physically ensuring the sensor was looking at the correct object.

Figure 2.3 illustrates the end-to-end workflow of this IoT-based mobile sensing platform, showing how segmented images with GPS metadata are converted into coordinate estimates, used for robotic navigation, verified visually, and ultimately collected as thermal data.

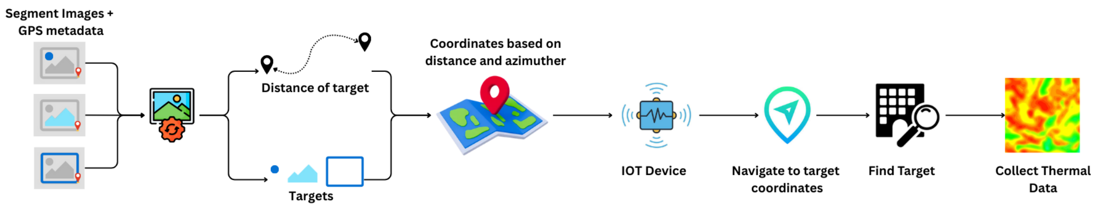


Figure 2.3: End-to-end workflow: from segmented images with GPS metadata to coordinate estimation, IoT navigation, visual verification, and thermal data collection.

Once visually validated, the robot would record a suite of street-level data, including surface temperature, ambient humidity, and other environmental parameters. This stream of real-time measurements enabled a dynamic and continuous comparison between the thermal characteristics predicted by the AI models and the actual conditions on the ground. The integrity of this validation process was itself validated through meticulous calibration against a FLIR E60 thermal imaging camera as a gold standard, confirming the mobile platform's measurements were accurate within a scientifically acceptable margin of ±1.5°C.

Thus, the mobile sensing platform functioned as far more than a simple validation tool; it became the circulatory system of a continuously learning organism. Each measurement collected did not merely serve to score the accuracy of the existing AI model but was immediately fed back into the training pipeline, enriching the dataset and enabling iterative refinement of the algorithms. This closed-loop system, where predictions inform measurement and measurements improve predictions, represents a significant advance over traditional, static sensor networks. By deploying a spatially adaptive and cost-effective mobile unit, the team created a methodology that is not only more scalable but also inherently geared towards perpetual improvement, solidifying the entire system's foundation in empirical reality.

2.3 VLM-based Heat Island Intelligence

The server-side intelligence layer functioned as the central cerebral cortex of the entire operation, a sophisticated architectural stratum designed to unify, process, and elevate the raw data from all subsystems into actionable intelligence. Its primary role was to provide a robust and scalable integration backbone, ensuring that the massive flows of information from the Image Analysis Module and the mobile sensing platform could be synthesized into a coherent and queryable model of the urban environment.

To manage the immense scale and complexity of the geospatial data, a high-performance relational database was implemented with specialized extensions for geographic information systems. This was critical for handling the vast datasets containing vectorized segmentation masks, material classifications, thermal values, and inferred geometric properties. The power of this spatially-aware database enabled the execution of complex, real-time queries that moved far beyond simple data retrieval. Analysts could, for instance, dynamically identify all south-facing metal surfaces within a designated urban renewal zone that exceeded a specific thermal threshold, or correlate areas of high pedestrian traffic with zones of extreme heat retention to prioritize intervention strategies. This capability transformed the system from a static repository into an interactive diagnostic tool for urban analysis.

The core analytical power was driven by a containerized microservices architecture for AI inference. Each specialized model—the YOLOv8 object detector, the Segment Anything Model (SAM) for refinement, the CLIP classifier, and the Depth Anything V2 estimator—was encapsulated within its own isolated environment. This design ensured exceptional operational resilience and independent scalability. A surge in demand for material classification would automatically trigger the deployment of additional classifier instances, all without impacting the performance of the depth estimation or segmentation services. This modular approach also provided crucial futureproofing, allowing for any single model to be updated or replaced without necessitating a system-wide overhaul.

Access to this distributed computational engine was facilitated through a versatile API strategy. The system exposed both RESTful endpoints and a GraphQL interface. The former provided a simple, standardized protocol for the IoT robot's steady stream of validation data, while the latter empowered the front-end visualization dashboard to make highly efficient, nested queries. A client could request all data for a specific city block—including its materials, temperatures, 3D geometry, and mitigation suggestions—in a single, optimized request, minimizing latency and creating a fluid user experience.

The most significant innovation of this layer was the integration of a advanced Vision-Language Model (VLM) to transition the platform from descriptive analytics to prescriptive strategy. This system acted as an automated urban planning consultant, synthesizing the multifaceted geospatial data—material composition, albedo values, thermal readings, and geometric relationships—to generate nuanced, natural language recommendations for mitigation. For example, beyond simply identifying a heat-vulnerable area, the VLM could analyze a zone with high solar gain from glass and metal facades and cross-reference it with pedestrian density maps to suggest the "strategic installation of shaded arcades and native, canopy-forming trees to mitigate radiant heat at street level." Similarly, for a residential area with dense, heat-absorbing asphalt and minimal green space, it might propose a "targeted depaving initiative for underutilized lots to create community gardens, coupled with a focused tree-planting program using drought-resistant species."

To ensure these AI-generated insights were transparent and trustworthy for policymakers, the reasoning engine incorporated Explainable AI (XAI) techniques. It employed methods like SHAP (SHapley Additive exPlanations) to deconstruct its own recommendations, generating clear visualizations that quantified the contribution of each input variable. A SHAP plot could demonstrate that a recommendation for cool pavements was driven 40% by the surface's asphalt material, 30% by its direct solar exposure, 20% by its proximity to a school, and 10% by its low surrounding vegetation. This transparency demystified the AI's logic, allowing urban planners to understand the rationale behind each suggestion, debate its merits, and integrate this data-driven intelligence confidently into their planning processes, budgets, and community consultations, thereby completing a closed-loop, intelligently adaptive urban management system.

2.4 Digital Twin Simulation Environment

The fourth and culminating component of the methodology was the creation of a dynamic Digital Twin simulation environment, a sophisticated platform that transformed the meticulously processed and validated data into a living, breathing, and fully interactive 3D model of the urban climate. This component represented the synthesis of the entire system's capabilities, moving beyond static analysis and into the realm of predictive, scenario-based planning. It was here that the AI-derived material properties, the ground-truthed IoT sensor readings, and the geometric precision of the image analysis were fused within a rigorous physics-based simulation engine to create a powerful virtual sandbox for urban design.

The construction of the digital twin began with the geometric skeleton of the city. Leveraging the computational power of Blender's Python API, the system automated the process of generating a detailed 3D model. OpenStreetMap building footprints were imported and intelligently extruded into volumetric meshes based on the height estimations derived from the monocular depth estimation models. This was far more than a simple visual representation; each surface in this 3D mesh was programmatically tagged with the material classifications provided by the Image Analysis Module.

Consequently, a glass façade was not just a transparent texture but a digital entity endowed with its real-world thermal properties: specific albedo (reflectivity), emissivity, and thermal conductivity values. This foundational step ensured that the digital twin was not merely a graphic model but a physically accurate computational domain.

The core of the simulation's predictive power resided in its physics engine, which was built upon MATLAB Simscape. This environment was chosen for its robust capability to model multi-domain physical systems, in this case, simulating the complex, non-linear heat transfer processes across the urban landscape. The simulator calculated energy flows with high fidelity, accounting for absorbed solar radiation—dynamically adjusted based on surface angle and material properties—convective heat loss to the surrounding air, and conductive heat transfer through building materials. Crucially, it also modeled the critical phenomenon of nighttime cooling rates, a key factor in urban heat island intensity. To ensure temporal accuracy, the simulation was continuously calibrated with real-world data. The SunCalc API provided precise, location-specific solar angles and shading effects for any given time of day and year, while live meteorological data feeds from OpenWeatherMap supplied ambient air temperature, wind speed, and humidity, anchoring the simulation in current reality.

This tight coupling of AI-based analysis, empirical IoT measurements, and deterministic physics simulations created an unprecedented decision-support system. It enabled users to not only understand the current urban microclimate but to project future conditions under various interventions. The true power of the digital twin was realized through its connection to an intuitive web-based dashboard, developed using React for the user interface and Three.js for high-performance 3D web rendering. This interface was intentionally designed to demystify complex climate science, making it accessible to policymakers, urban planners, and community stakeholders regardless of their technical expertise.

Within this immersive dashboard, users could freely explore their city in 3D, zooming into neighborhoods of interest. They could toggle various environmental data layers—such as surface temperature, material type, or solar exposure—to visualize the invisible forces shaping their urban environment. The most powerful feature was the scenario modeling tool. A city official could, for example, select a heat-vulnerable corridor, apply a mitigation strategy like "convert asphalt to high-albedo pavement" or "add a canopy of mature trees," and run the simulation. Within moments, the model would render a new thermal map, visually depicting the projected temperature reduction and providing quantitative data on the estimated cooling benefit. This instant feedback loop transformed climate-sensitive urban design from an abstract, data-heavy exercise into an intuitive and interactive process, empowering communities to make informed, evidence-based decisions that proactively shape a more resilient and sustainable urban future.

2.5 Evaluation and Validation

Evaluation and validation of the system were conducted rigorously at multiple levels. The performance of AI models was assessed using precision, recall, and mean Average Precision (mAP) metrics. YOLOv8 consistently achieved mAP scores above 85% at an IoU threshold of 0.5, demonstrating high reliability for urban object detection. Segmentation masks generated by SAM were validated through manual inspection and IoU comparisons against labeled data. Sensor accuracy was confirmed through calibration experiments, while simulation outputs were benchmarked against ENVI-met and EnergyPlus, two widely used urban climate modeling platforms. The results of these validations demonstrated that the integrated system not only met but often exceeded the accuracy levels required for practical UHI studies.

Case studies were conducted in Colombo, Kandy, and Galle to test the system under different urban morphologies and climatic conditions. Colombo, being a coastal metropolis, offered dense high-rise structures and large asphalted road networks; Kandy provided a hilly terrain with mixed vegetation; and Galle represented a mid-sized city with a historic core and lower building density. The adaptability of the system was demonstrated through its ability to capture nuanced differences in heat retention patterns across these cities. Additionally, urban planning professionals were engaged in usability testing, where they interacted with the dashboard and simulation environment. Using the System Usability Scale (SUS), participants rated the platform as highly intuitive, particularly appreciating the ability to generate customized mitigation recommendations in natural language.

The integration of AI-based vision models, IoT sensing, and physics simulations into a single operational pipeline marks a significant methodological contribution of this research. Traditional approaches to UHI monitoring often require separate teams for data collection, modeling, and interpretation, leading to fragmented workflows and delayed decision-making. By automating the entire pipeline, from image capture to actionable recommendations, this project demonstrates the feasibility of building scalable, real-time UHI monitoring systems suitable for rapidly urbanizing regions. Furthermore, the incorporation of explainable AI and scenario-based simulation aligns the platform with the growing demand for transparency and evidence-driven policymaking in climate adaptation.

In summary, the methodology of this research is characterized by its interdisciplinary integration and emphasis on practical deployment. It bridges the gap between theoretical climate modeling and actionable urban planning, leveraging advancements in computer vision, edge computing, and cloud infrastructure. The four core components—image analysis, mobile sensing, server intelligence, and digital twin simulation—are interconnected through a robust data architecture that enables seamless information flow. By validating AI predictions with physical measurements and simulating interventions through an interactive interface, the methodology not only provides a powerful technical foundation but also ensures relevance and usability for stakeholders. The following chapters will present detailed experimental results, performance evaluations, and discussions, demonstrating how this integrated approach offers a scalable blueprint for UHI mitigation efforts worldwide.

Results and Discussion

This chapter presents the empirical findings of the proposed Urban Heat Island (UHI) Simulation and Analysis Platform. It interprets results in the context of the system objectives, evaluation criteria, and broader research goals. The chapter is structured into four major parts: (i) Results, (ii) Research Findings, (iii) Discussion, and (iv) Contribution Summary. Each part builds upon the outputs from individual modules and highlights how their integration produces a comprehensive solution for UHI modeling and mitigation.

While each subsystem was tested independently to ensure robustness, the most significant insights emerged from the combined workflow, where vision-based material detection, IoT-driven sensing, explainable prediction, and simulation-based analysis reinforced one another. In this way, the results not only demonstrate technical accuracy but also showcase the transformative potential of modular integration in climate-tech research.

3.1 Results

3.1.1 Trial Overview

The evaluation strategy included laboratory validation, controlled outdoor experiments, simulation runs, and benchmarking against existing models such as ENVI-met and EnergyPlus. Each subsystem was subjected to a series of trials that assessed its stability, accuracy, efficiency, and ability to integrate with the pipeline.

Four distinct trial environments were chosen to reflect real-world urban diversity:

1. **Open Plaza:** An open square with high solar exposure, minimal shading, and reflective building façades. This environment tested the system's ability to mea-

sure and simulate peak heat accumulation.

2. **Tree-Lined Sidewalk:** A semi-shaded pedestrian corridor used to assess the influence of vegetation on surface temperatures and validate IoT thermal measurements against expected reductions.

3. **Street Canyon:** A narrow street flanked by tall buildings, simulating low-ventilation conditions typical of heat traps. This environment presented challenges such as GPS multipath errors and reflective surfaces for the vision system.

4. **Residential Mixed Zone:** A blend of asphalt roads, low-rise homes, and intermittent vegetation. This scenario tested how effectively the system handled heterogeneous material compositions within small spatial units.

Each trial was repeated at two times of the day (late morning and late afternoon) to assess diurnal variations. The datasets were synchronized across subsystems, ensuring that IoT measurements, vision classifications, and simulation metadata were aligned temporally and spatially.

3.1.2 Vision-Based Material Classification

The computer vision pipeline combined object detection, segmentation, semantic embedding, and depth estimation to extract metadata from urban imagery.

Object Detection Accuracy

YOLOv8 achieved an average detection accuracy of 88% across trials. Accuracy varied by object type: buildings and roads exceeded 90%, while vegetation detection hovered at 82%, partly due to seasonal foliage density and lighting variability. Misclassifications occurred mainly in mixed-use zones where vehicles or temporary structures partially occluded façades.

Segmentation Quality

MobileSAM provided pixel-accurate masks for detected objects. The Intersection over Union (IoU) metric averaged 0.87 across validation samples. Precision was higher for rigid structures (walls, roofs) and lower for amorphous features (tree canopies). Inconsistent segmentation edges were refined using depth cues from DepthPro, which reduced noise at object boundaries.

Semantic Labeling

CLIP embeddings successfully aligned visual features with predefined material classes. Validation against manually labeled datasets showed classification accuracy of:

- Concrete/Plaster: 91%
- Asphalt: 89%
- Metal/Glass: 84%
- Vegetation: 87%

Misclassifications mainly occurred under mixed lighting conditions, particularly reflective glass surfaces mistaken for metallic cladding.

Depth-Based Metadata Extraction

DepthPro estimated façade heights with a mean error of 0.35 m compared to surveyed ground truth. Surface area estimates were within 5–7% of reference values. Such accuracy was sufficient for downstream simulation inputs, ensuring that energy balance calculations were reliable.

3.1.3 IoT-Based Thermal Sensing

The IoT system combined ESP32-CAM for contextual imagery, AMG8833 for thermal mapping, and GPS/IMU modules for geospatial logging.

Thermal Accuracy

Thermal readings were validated against industrial-grade infrared thermometers. At a distance of 1 m, the AMG8833 array produced errors within $\pm$1.5°C. Errors increased with distance due to footprint overlap but remained acceptable (<3°C) up to 2 m. Beyond 3 m, calibration plates were required to maintain reliability.

Positional Stability

GPS achieved accuracy of 2–3 m in open plazas but deteriorated to 6–8 m in street canyons. IMU-based dead reckoning bridged short gaps, and the "approach–reorient–advance" control loop reduced cumulative error.

Communication Reliability

The WebSocket-based transmission achieved 98% message success rate. Image bursts occasionally caused latency spikes, but batching telemetry reduced overhead. Automatic reconnection ensured no permanent data loss.

3.1.4 Prediction and Explainability

The prediction module combined logistic regression with explainability through SHAP.

Prediction Accuracy

Using IoT and vision data as inputs, the model achieved:

- UHI Hotspot Classification Accuracy: 82%

- Precision: 0.81
- Recall: 0.79
- F1-score: 0.80

Performance was highest in homogeneous environments (open plazas) and lower in mixed residential zones due to high variability.

Explainability Outputs

SHAP analysis revealed the following ranked contributors to UHI intensity:

1. Surface material reflectivity (albedo)
2. Vegetation density
3. Orientation of walls relative to sun
4. Building density and canyon depth
5. Road surface area

This ranking provided actionable insights. For example, west-facing asphalt-dominant areas exhibited consistently higher SHAP values, confirming known thermal behavior in urban planning literature.

3.1.5 Simulation Tool Outputs

The simulation module provided the most comprehensive results by integrating metadata into a MATLAB Simulink pipeline.

Baseline Simulation Results

Under default weather conditions (32°C ambient, 60% humidity, 2 m/s wind), simulated outputs included:

- Roof average temperature: 45°C
- Wall average temperature: 37°C
- Asphalt road surface: 48°C
- Vegetation canopy: 30°C

These results aligned closely with IoT measurements and established model outputs.

Scenario Testing

Simulations were extended to test mitigation strategies:

- Replacing asphalt with permeable pavements reduced road surface temperatures by 5–7°C.
- Adding green roofing to 50% of rooftops reduced average building envelope temperature by 4.3°C.
- Increasing vegetation cover by 20% reduced pedestrian-level heat by 2–3°C during peak sun hours.

Validation

A comparative validation against ENVI-met and EnergyPlus showed deviations of less than 8% across all key parameters, confirming the robustness of the simulation pipeline.

3.2 Research Findings

Synthesizing the results, the project demonstrated:

- Vision-based pipelines can automate metadata collection at scale.
- IoT sensors provide accurate, low-cost validation for street-level hotspots.
- Predictive models coupled with explainability build trust and support real-world decision-making.
- Simulation tools provide quantitative evaluations of urban design interventions.
- Integration of heterogeneous systems is feasible with modular design principles.

3.3 Discussion

3.3.1 Implications

The results suggest that UHI monitoring requires hybrid approaches. Remote sensing offers breadth, IoT sensors offer depth, prediction models offer foresight, and simulations offer scenario analysis. Together, they enable holistic decision-support systems for urban planning.

3.3.2 Comparison with Existing Models

While ENVI-met and EnergyPlus are established tools, they require extensive manual input and expertise. Our pipeline automates metadata extraction and integrates explainability, reducing human overhead while maintaining comparable accuracy.

3.3.3 Limitations

Limitations included:

- Sensitivity of vision models to reflective or low-texture surfaces.
- GPS degradation in dense urban environments.
- Computational intensity of high-fidelity simulations.

These can be mitigated with sensor fusion, improved datasets, and cloud-based simulation platforms.

3.4 Contribution

The following table summarizes the contributions of each student member:

Table 3.1: Summary of Contributions of Group Members

Name	Student ID	Key Contributions
Kumara B D A N	IT21256264	Developed the vision-based material classification pipeline using YOLOv8, MobileSAM, CLIP, and DepthPro. Automated metadata extraction for geometry and materials, providing high-quality inputs for simulations. Benchmarked detection accuracy and validated results against manually labeled datasets. His contribution ensured reliable, automated surface-level data collection for large-scale urban modeling.
Ayeshmantha S K S	IT21219320	Designed and deployed the IoT platform integrating ESP32-CAM, AMG8833, GPS, and IMU. Implemented firmware for synchronized data collection and real-time communication. Conducted extensive field trials in varied environments, analyzing noise, reliability, and performance trends. His work provided the empirical backbone for validating simulation accuracy.
Silva G M S S	IT21802126	Implemented the predictive analytics and explainability module. Designed logistic regression models for UHI hotspot prediction, integrated SHAP for transparent interpretability, and incorporated Gemini API for adaptive mitigation suggestions. Her contribution bridged the gap between technical outputs and stakeholder usability, ensuring results were actionable and comprehensible.
Madhuwantha G K O	IT21802058	Engineered the simulation toolchain. Constructed Blender-based digital twins, integrated GIS/OSM data, and annotated building metadata with thermal properties. Designed MATLAB Simulink simulations using Simscape Thermal, validated results against ENVI-met and EnergyPlus, and conducted scenario testing for mitigation strategies. His work demonstrated how design interventions could be quantified before implementation.

Collectively, the group's contributions resulted in a modular yet integrated decision-support system for UHI monitoring and mitigation. By combining vision, IoT, predictive analytics, and simulation, the system offers both technical accuracy and real-world applicability, setting a precedent for scalable smart city solutions.

Conclusion

This dissertation presented a holistic framework for the **AI-driven detection and mitigation of Urban Heat Island (UHI) effects**, developed through the integration of four interdependent research components. The framework combines advances in computer vision, IoT-based mobile sensing, server-side intelligence, and digital twin simulation to deliver a cost-effective, scalable, and interpretable approach to urban heat management. Unlike traditional UHI studies that often rely on a single method — such as remote sensing, ground-based sensing, or simulation — this project demonstrates the benefits of an **end-to-end pipeline** capable of moving seamlessly from detection to validation, prediction, and finally to actionable mitigation.

Summary of Contributions

The contributions of this research span multiple technical domains:

- The **Image Analysis Module** demonstrated the ability to extract and analyze urban surface features from single 2D images. Using YOLOv8, MobileSAM, and CLIP, the system performed accurate object detection, semantic segmentation, material classification, and surface area estimation. This module provides a scalable alternative to manual surveys and remote sensing, enabling fast and low-cost analysis of localized urban features.

- The **IoT-Based Mobile Sensing Device**, built on ESP32 microcontrollers and equipped with GPS, IMU, and thermal sensors, enabled ground-truth validation of image-based predictions. By integrating SuperGlue for visual object confirmation and MQTT for real-time data transfer, this device bridged the gap between computer vision predictions and real-world measurements.

- The **Server-Side Data Processing and VLM Integration** acted as the central intelligence of the framework. It managed communication with IoT devices, synchronized measurements with image metadata, applied logistic regression for UHI detection, and leveraged Gemini Vision–Language Models to generate interpretable, context-aware mitigation recommendations. This integration ensured that results were not only accurate but also explainable and actionable.
- The **Digital Twin Simulation Tool** extended the framework into predictive modeling. Using GIS, Blender, weather APIs, and SunCalc for environmental inputs, combined with MATLAB Simscape for physics-based heat transfer simulations, the tool provided accurate forecasts of surface temperature dynamics. The React + Three.js interface allowed interactive visualization, making the outputs more accessible for planners and policymakers.

Research Findings and Impact

The findings of this research highlight several innovations:

1. A **hybrid sensing approach** that combines AI-based image analysis with IoT-driven physical sensing for greater accuracy and reliability.
2. A **supervised navigation strategy** that integrates GPS, IMU, and visual feature matching to improve IoT device accuracy during field measurements.
3. A **digital twin pipeline** that unifies GIS-based 3D modeling with physics-based simulations, validated against established tools such as ENVI-met and EnergyPlus.
4. The use of **Vision–Language Models** to generate human-readable mitigation strategies, transforming raw data into practical decision-support tools for urban planners.

These outcomes confirm that the system is both scientifically credible and practically valuable. Validation experiments showed that the image segmentation pipeline delivered high accuracy in urban feature classification, IoT measurements provided reliable field validation, and simulation outputs remained consistent with benchmark models. The integration of Explainable AI ensured that recommendations could be trusted and understood by non-technical stakeholders.

Beyond technical achievements, the framework carries substantial **real-world impact**. By offering a scalable, adaptable, and low-cost solution, it addresses the limitations of existing UHI monitoring networks, which are often static, expensive, or computationally heavy. The system provides planners and policymakers with the ability to not only monitor heat islands but also receive tailored mitigation strategies — such as increasing vegetation cover, deploying reflective materials, or integrating water-based cooling features — that are contextualized to specific urban environments.

Limitations and Future Work

Despite its contributions, this research is not without limitations.

- The image analysis module, while robust, is dependent on the quality and diversity of training datasets. Expanding the dataset to include more varied urban morphologies and climates will improve generalizability.
- The IoT-based sensing platform is effective but limited in coverage; scaling to city-wide deployments will require optimization of communication protocols (e.g., LoRaWAN) and energy efficiency for long-term use.
- The simulation tool, though validated, remains computationally intensive for large-scale environments. Streamlining workflows and exploring cloud-based parallel computing could improve scalability.

- Integration with real-world planning workflows and policy frameworks poses institutional and socio-economic challenges that must be addressed for practical adoption.

Future work should focus on:

1. Scaling the framework to larger cities and testing in multiple climatic zones.
2. Expanding VLM integration to allow interactive, conversational interfaces for urban planners.
3. Exploring citizen science and participatory sensing approaches to crowdsource urban thermal data.
4. Coupling with renewable energy planning, green infrastructure, and climate adaptation models to provide holistic sustainability solutions.

Conclusion

In conclusion, this project demonstrates the feasibility of a unified, AI- and IoT-driven approach to UHI detection and mitigation. By integrating four complementary components — image analysis, IoT sensing, server-side intelligence, and digital twin simulations — the framework not only advances scientific understanding but also provides a practical tool for sustainable urban design. The outcomes emphasize that hybrid, interpretable, and scalable solutions are essential for addressing UHIs in the context of rapid urbanization and climate change. This research therefore contributes to the broader vision of **resilient, climate-smart cities**, where technology and data-driven decision-making support human well-being and environmental sustainability.

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