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Innovative Design Synthesis: AI-Driven Solutions for Sustainable Urban Planning: Development, Evaluation, and Insights

*¹ Dr. Koudoua Ferhati , ² Ahmed M. Elgohary , ³ Ahmed N. Elghar , ⁴ Ahmad S. Abdelaal , ⁵ Ahmed M. Kamel , ⁶ Mohamed A. Elsayed , ⁷ Ahmed E. Sheimy , ⁸ Mena E. Habib

¹ Department of Project management, Faculty of Architecture and Urbanism, Constantine 3 University, Algeria

²⁻⁸ Department of Research and Development, MIRANDO Solutions, Egypt

¹ E-mail: koudoua.ferhati@univ-constantine3.dz, ² E-mail: Elgohary@mirandosolutions.com, ³ E-mail: Anader370@gmail.com,

⁴ E-mail: Ahmadsameh010@gmail.com, ⁵ E-mail: Amostafaarslan@gmail.com, ⁶ E-mail: Elsayadmohamed396@gmail.com,

⁷ E-mail: Ahmedamad456478@gmail.com, ⁸ E-mail: Menaesam76@gmail.com

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ABSTRACT



This research aims to explore the capabilities of Artificial Intelligence model applications in sustainable urban planning design, aiming to create an AI-powered model that detects urban sprawl, urban decay, infrastructure deficiencies, and environmental degradation, and generates sustainable solutions. The methodology includes model development, data preprocessing, architecture design, training, and comprehensive questionnaire design and statistical analysis. Insights into the model's performance and perception were gathered from 200 participants, including researchers, developers, architects, and urbanists. Results reveal significant variations in perceived model performance across demographic groups. Statistical tests and correlations study showed that participants from urban areas rated the model's effectiveness in detecting urban sprawl significantly higher than those from rural areas, and urban planners found the model's infrastructure deficiency detection less accurate compared to architects. These findings provide valuable guidance for enhancing urban planning strategies and underscore AI's potential in transforming urban planning with more effective and inclusive solutions.

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Highlights:

- Developed an AI-driven model that integrates real-time data and multimodal analysis for urban problem detection.
- Demonstrated superior performance compared to traditional GIS-based approaches and recent machine learning models.
- Addressed key urban issues such as urban sprawl, decay, infrastructure deficiencies, and environmental degradation.
- Contributed a novel methodological framework combining supervised and self-supervised learning for urban analysis.

Contribution to the field statement:

This study advances urban planning literature by integrating AI-driven methodologies with traditional urban analysis. Our novel model combines real-time data integration with multimodal analysis, offering dynamic, data-driven insights that surpass the capabilities of traditional GIS and recent machine learning models. This research contributes unique methodological advancements and practical applications, enhancing urban problem detection and decision-making processes.

*Samruddhi Purohit:

Department of Architecture, MKSSS' Dr. Bhanuben Nanavati College of Architecture for Women, India

Email address: a19104.samruddhip@bnca.ac.in

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1. Introduction

1.1 Background and Context

The accelerating pace of urbanization and the escalating threats of climate change and resource depletion underscore the urgent need for sustainable urban development (Li et al., 2022). Cities, as major contributors to environmental degradation, require strategies for creating sustainable, resilient, and livable urban environments (Bibri et al., 2024; Paris et al., 2023). Traditional urban planning and architectural design often struggle to balance built form, environmental impact, and human well-being (Fallmann & Emeis, 2020; Ferramosca & Terracciano, 2023).

1.2 Previous AI Applications in Urban Planning

Previous attempts to integrate AI in urban planning have shown promise but also highlighted limitations. AI has emerged as a transformative force within architecture and urban planning, revolutionizing design, planning, and sustainability (Regona et al., 2024). The early adoption of AI in these fields dates back to the 1960s with computer-aided design (CAD) and automated drafting, evolving to include generative design and optimization (Zhang et al., 2023). Notable examples include the Metropol Parasol in Seville, Spain, and the Masdar City project in the UAE, which utilized AI for design and sustainability (Ersen et al., 2022; Auwalu & Bello, 2023). In urban design, AI has been applied to traffic management and public transportation optimization, with smart city initiatives like Singapore leveraging AI for infrastructure and service optimization (Herath & Mittal, 2022; Sons et al., 2023). AI tools have enabled architects and urban planners to enhance building efficiency, reduce energy usage, and minimize environmental impact (Almaz et al., 2024). The creation of digital twins allows for real-time monitoring and simulation, ensuring designs meet sustainability goals (Omran et al., 2023). However, despite these advancements, there are discrepancies between perceived benefits and actual adoption rates, and some scepticism remains among practitioners (Dwivedi, Kshetri, et al., 2023). Milestones include the development of a reinforcement learning model for urban planning by Tsinghua University (Peng et al., 2023) and advancements in automated design optimization (Rafsanjani & Nabizadeh, 2023). Case studies like The Edge in Amsterdam and Sidewalk Labs in Toronto exemplify successful AI-driven sustainable design, while best practices include generative design and biophilic design integration (Edge, n.d.; Goodman & Powles, 2019; Smorzhnikov & Ignatova, 2021; Ramm et al., 2024). These examples underscore AI's potential to drive sustainable design solutions in architecture and urban planning (Bibri, Huang, & Krogstie, 2024; Berčič et al., 2024).

1.3 Gap identification

While traditional methods face limitations, integrating cutting-edge AI methods into urban design processes offers a promising solution. Existing AI applications in urban planning, such as traffic optimization and land-use analysis, often lack the comprehensive capability to address broader sustainability concerns (Bibri, Huang, et al., 2024). This study aims to investigate the transformative potential of AI-driven models in the design and inhabitation of built environments, addressing gaps in current methodologies.

1.4 Research objectives

The primary objective of this research is to conceptualize and develop an AI-driven model that detects urban problems like urban sprawl, urban decay, infrastructure deficiencies, and environmental degradation, and suggests innovative, sustainable solutions. Specifically, the study will:

1. Harness the generative capabilities of GANs and the semantic understanding of language models to create a novel AI-driven model.
2. Assess the model's performance through a questionnaire-based evaluation process with experts in urban planning and development.

3. Evaluate the model's effectiveness in addressing urban challenges and its potential to revolutionize design practices.

1.5 Significance of the study

This study examines the convergence of AI and urban planning to catalyze a paradigm shift in urban development (John-Nsa et al., 2023b). Beyond technical innovation, the research emphasizes the importance of human-centred design in shaping our built environment. The outcomes of this research are expected to extend beyond academia, inspiring a new generation of urban planners and policymakers to create sustainable, equitable, and resilient cities (Kanyepe, 2023).

By adopting an interdisciplinary approach that integrates urban expertise with AI-driven computational design methodologies, this research contributes significantly to academia by advancing the discourse on sustainable urban development. It charts a course toward a future where sustainability, innovation, and social responsibility converge, fostering the development of urban environments that are not only more intelligent but also more sustainable, inclusive, and conducive to quality living. This research not only enhances the theoretical framework surrounding urban studies but also provides empirical insights that can inform future academic inquiry and policy-making in the field of urban planning and design.

2. Materials and Methods

This study is grounded in two key theories: Urban Systems Theory and Multimodal Learning Theory. Urban Systems Theory allows for a nuanced understanding of the complexities inherent in urban environments (Batty, 2013; Jiang, 2017), while Multimodal Learning Theory enhances the model's capacity to analyze diverse data sources effectively (Kress, 2010; Alper et al., 2020). The methodological processes outlined in the chart (Figure 1) include data collection, preprocessing, model architecture, training procedures, and evaluation metrics, which collectively contribute to the robustness and efficacy of the urban problem detection model. This comprehensive framework supports the overarching goal of developing an innovative and responsive solution to urban challenges, ensuring that both theoretical and practical considerations are addressed throughout the research process.

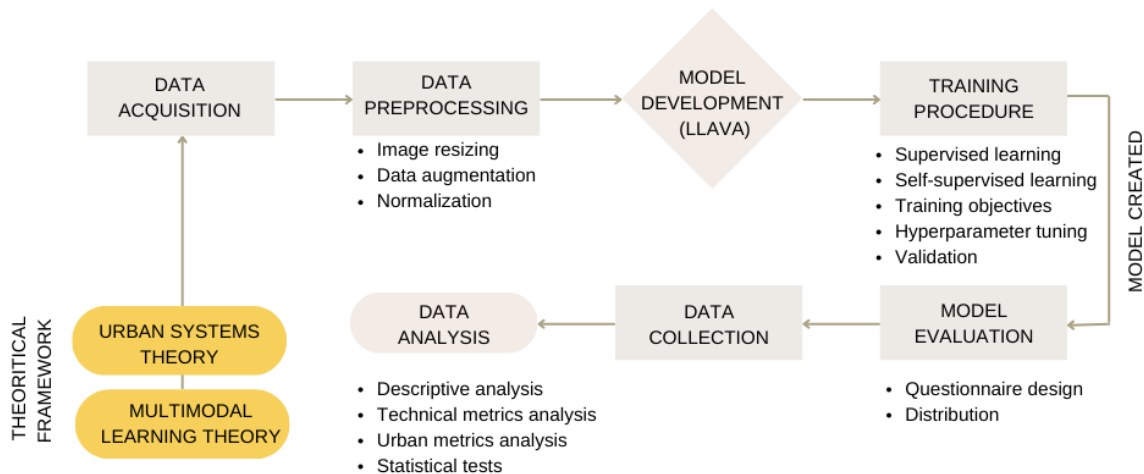


Figure 1. Theoretical and Methodological Framework.



2.1 Model development

2.1.1 Data Collection

The dataset employed for model testing is the UC Merced Land Use Dataset, which features 21 land use categories. It includes 100 images per category, each with dimensions of 256x256 pixels. These images were manually selected from larger images in the USGS National Map Urban Area Imagery collection, covering various urban regions across the country. This dataset was chosen due to its comprehensive representation of land use types relevant to urban planning, making it an ideal benchmark for detecting urban issues globally.

2.1.2 Preprocessing

The preprocessing steps for the dataset include:

- **Image resizing:** The images were adjusted to a consistent size of 256x256 pixels, ensuring uniformity across the dataset and facilitating more efficient model training.
- **Data augmentation:** The dataset was augmented by applying random transformations such as rotation, flipping, and colour jittering to the images, which enhances the model's robustness by providing a wider variety of training samples and helping to prevent overfitting.
- **Normalization:** The pixel values of the images were scaled to a standard range, specifically between **0 and 1**. This step is crucial as it ensures that the model converges faster during training and improves the overall performance by reducing the risk of numerical instability.

2.1.3 Model Architecture

The model used for this task is the LLaVA (Large Language Model for Visual Analysis) model, which is a multimodal transformer-based model that combines the capabilities of a large language model with those of a computer vision model. The architecture consists of an **encoder** and a **decoder**, where the encoder is responsible for processing the input image and the decoder generates the corresponding output text. The model utilizes attention mechanisms to focus on specific parts of the input image and associated text, allowing for more accurate associations between visual elements and textual descriptions. The training employs **transfer learning** strategies, leveraging pre-trained weights from existing models to enhance the learning process.

2.1.4 Training Procedure

The model was trained using a blend of supervised and self-supervised learning methods. The supervised learning aspect includes training the model on an extensive dataset of labeled images paired with corresponding text descriptions (Zhao et al., 2024). The self-supervised learning component entails training the model on a large dataset of unlabeled images, with the model's predictions serving as labels. The training objectives included:

- a- Masked language modelling:** The model was trained to forecast the missing words in sentences enhancing its understanding of language context.
- b- Image-text matching:** The model was trained to match the input image with the corresponding text description.
- c- Visual reasoning:** The model was trained to analyze the input image and generate a text description that explains the observed elements in the image, aiding in the identification of urban issues...

The model was utilizing a batch size of 32 and a learning rate of 1e-5. The training process was conducted for 10 epochs, with the model being evaluated on a validation set after every epoch to monitor performance and prevent overfitting.

d- Zero-Shot Prompting:

The model was used for zero-shot prompting, where the model received a prompt and was required to produce a response without any additional training data. The prompt used for this task was:

"Analyze the image and indicate whether each of the following urban problems is present, providing reasoning based on the visual cues observed. Respond with 'Yes' or 'No' for each problem and explain your reasoning."

The model was able to generate responses for each of the urban problems, providing reasoning based on the visual cues observed in the image.

2.2 Model Evaluation

The evaluation framework for the generated designs is made using a questionnaire that includes both technical and urban metrics to assess their performance.

2.2.1 Questionnaire design

A structured questionnaire is developed to collect data on demographic information, technical metrics feedback, and urban metrics feedback. To extract quantitative results from the study, we designed it using the following metrics alongside the demographic information like age, gender, education and country:

- **Accuracy:** Measure the model's overall correctness in identifying urban problems correctly (Chaudhuri & Clarke, 2013).
- **Precision:** Evaluate the ability to identify urban problems without false positives (Safabakhshpachehkenari & Tonooka, 2023).
- **Recall:** Assess the capability of identifying the instances of urban problems present in the images (Safabakhshpachehkenari & Tonooka, 2023).
- **F1 Score:** Combine precision and recall to provide a balanced evaluation of the model's performance (Chaudhuri & Clarke, 2013).
- **Confusion Matrix:** Offer insights into the model's performance by showing true positives, true negatives, false positives, and false negatives (Chaudhuri & Clarke, 2013).
- **Feature Importance:** Analyze the importance of visual cues/features in detecting urban problems to understand which cues contribute most significantly to the model's decisions (Chaudhuri & Clarke, 2013).

In addition to the technical metrics, we added to the evaluation questionnaire urban metrics that can quantify the urban problems detection of the model per image:

- **Urban Sprawl Detection Rate (USR):** Calculate the percentage of images correctly identified as exhibiting urban sprawl out of the total images labelled as having urban sprawl (Sonde et al., 2020).

$$USR = \frac{TP_{sprawl}}{TP_{sprawl} + FN_{sprawl}}$$

where TP_{sprawl} is the number of true positives for urban sprawl, and FN_{sprawl} is the number of false negatives for urban sprawl.

- **Urban Decay Detection Rate (UDR):** Measure the proportion of images correctly identified as displaying urban decay out of the total images labelled as having urban decay (Vallebuena & Lee, 2023).

$$UDR = \frac{TP_{decay}}{TP_{decay} + FN_{decay}}$$

where TP_{decay} is the number of true positives for urban decay, and FN_{decay} is the number of false negatives for urban decay.

- **Infrastructure Deficiencies Detection Rate (IDR):** Determine the percentage of images correctly identified as indicating infrastructure deficiencies out of the total images labelled as having infrastructure deficiencies (Kanyepe, 2023)

$$IDR = \frac{TP_{infra}}{TP_{infra} + FN_{infra}}$$

Where TP_{infra} is the number of true positives for infrastructure deficiencies, and FN_{infra} is the number of false negatives for infrastructure deficiencies.

- **Environmental Degradation Detection Rate (EDR):** Compute the proportion of images correctly identified as showing environmental degradation out of the total images labelled as having environmental degradation (Khatun, 2017).

$$EDR = \frac{TP_{env}}{TP_{env} + FN_{env}}$$

Where TP_{env} is the number of true positives for environmental degradation, and FN_{env} is the number of false negatives for environmental degradation.

2.2.2 Population Selection

The study targets a diverse population comprising 200 individuals, including researchers, developers, architects, and urbanists. This sample size was determined based on statistical power analysis, indicating that a minimum of 200 responses would provide sufficient power to detect significant differences in urban metrics across various demographic groups, ensuring the results are representative of the broader population in urban planning contexts.

2.2.3 Questionnaire Distribution and Data Collection

- **Distribution:** The questionnaire is distributed electronically via email or online survey platforms to the identified population. Participants are invited to complete the questionnaire voluntarily.
- **Data Collection:** Responses from participants are collected over a specified time period, ensuring adequate representation from each demographic category.

2.2.4 Data Preparation

- **Cleaning:** The collected data is cleaned to address any inconsistencies or missing values.
- **Coding:** Likert scale responses for technical and urban metrics are coded numerically for analysis purposes.

2.2.5 Data Analysis

- **Descriptive Analysis:** Analyzed descriptively to characterize the study population.
- **Technical Metrics Analysis:** To comprehend the central tendencies and variability of each technical metric, we calculate fundamental descriptive statistics. This analysis enables a clear understanding of the distribution and characteristics of these metrics.
- **Urban Metrics Analysis:** Mean scores for urban metrics feedback (urban sprawl detection rate, urban decay detection rate, infrastructure deficiencies detection rate, environmental degradation detection rate) are computed and compared across degrees of consent.

2.2.6 Statistical Tests

- **Correlation Analysis:** To explore relationships between demographic variables and Likert scale responses for technical and urban metrics.

3. Results

3.1 Model Performance

To present the model's outcome results we start with the main used prompt:

USER: <image>\n

Analyze the image and indicate whether each of the following urban problems is present, providing reasoning based on the visual cues observed. Respond with 'Yes' or 'No' for each problem and explain your reasoning.

Urban Problems:

Urban Sprawl: (Yes/No) Reasoning:

Urban Decay: (Yes/No) Reasoning:

Infrastructure Deficiencies: (Yes/No) Reasoning:

Environmental Degradation: (Yes/No) Reasoning: """"

For this prompt, we present the following examples (01, 02 and 03):



Figure 2. Example 01, 02 and 03.

Model response for example 01:

- ✓ Urban Sprawl: Yes. Reasoning: The image shows a large number of cars parked on the street, which indicates that the area is densely populated. This suggests that the urban area is experiencing urban sprawl, where the city expands outward, leading to increased population density and limited space for infrastructure development.
- ✓ Urban Decay: No. Reasoning: The image shows a well-maintained street with cars parked neatly, indicating that the area is well-cared for and not experiencing any signs of urban decay.
- ✓ Infrastructure Deficiencies: No. Reasoning: The image shows a well-maintained street with cars parked neatly, indicating that the infrastructure in the area is well-developed and not experiencing any deficiencies.
- ✓ Environmental Degradation: No. Reasoning: The image shows a well-maintained street with cars parked neatly, indicating that the area is not experiencing any signs of environmental degradation.

Model response for example 02:

- ✓ Urban Sprawl: Yes. Reasoning: The presence of multiple cars parked in the parking lot indicates that the building is a commercial or office building, which is a common characteristic of urban sprawl.
- ✓ Urban Decay: No. Reasoning: The building appears to be well-maintained and in good condition, which suggests that it is not experiencing urban decay.
- ✓ Infrastructure Deficiencies: No. Reasoning: The parking lot is well-maintained, and there are no visible signs of neglect or deterioration, which indicates that the infrastructure is not deficient.
- ✓ Environmental Degradation: No. Reasoning: The building is surrounded by trees, which suggests that the area is not experiencing significant environmental degradation.

Model response for example 03:

- ✓ Urban Sprawl: Yes. The image shows a street with many houses and cars, indicating that the area is densely populated and has likely expanded beyond its original boundaries.
- ✓ Urban Decay: Yes. The image shows a street with many houses and cars, indicating that the area is densely populated and has likely expanded beyond its original boundaries.
- ✓ Infrastructure Deficiencies: Yes. The image shows a street with many houses and cars, indicating that the area is densely populated and has likely expanded beyond its original boundaries.
- ✓ Environmental Degradation: No. The image shows a street with many houses and cars, indicating that the area is densely populated and has likely expanded beyond its original boundaries. However, there is no clear indication of environmental degradation in the image.

3.2 Model evaluation

This section presents the results of the model evaluation questionnaire, which was distributed to assess the performance of the urban problems detection model. Out of 200 questionnaires sent, 132 were completed and returned, resulting in a response rate of 66%. The analysis is divided into three main parts: demographic characteristics, technical metrics, and urban metrics.

3.2.1 Descriptive Analysis

The following section presents descriptive statistics summarizing the demographic characteristics of the participants involved in the evaluation of the urban problems detection model.

a- Age: Figure 3 displays the age distribution frequencies of participants in the study, categorized into three age ranges: 18-24, 25-44, and 45-64. It shows the frequency and percentage of participants in each age group, along with valid and cumulative percentages. The majority of participants (37.1%) fall within the 25-44 age range, followed by those aged 18-24 (34.1%) and 45-64 (28.8%).

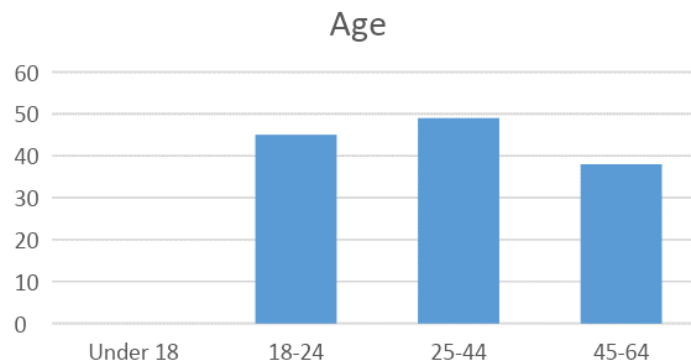


Figure 3. Age distribution.

b- Gender: Figure 4 shows the gender distribution of participants, divided into Male and Female categories. It indicates that 56.8% of participants are Male, while 43.2% are Female.

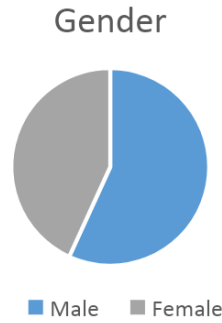


Figure 4. Gender distribution.

c-Education: Figure 5 displays the education level frequency distribution of participants, categorized into four groups. It shows the percentage of participants in each category, with the highest proportion having a Bachelor's degree (28.8%), followed by a Doctorate (23.5%), High school (28.0%), and Master's degree (19.7%).

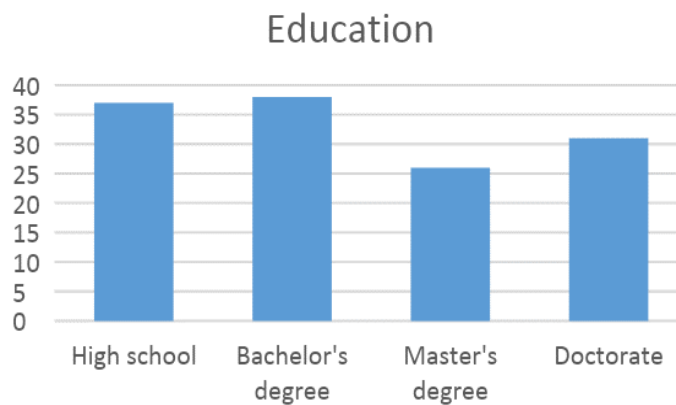


Figure 5. Education level.

d-Country : Figure 6 shows the distributions by country. It indicates the percentages from each country, with Algeria (14.4%), Egypt (12.1%), and Romania (15.9%) being the most represented.

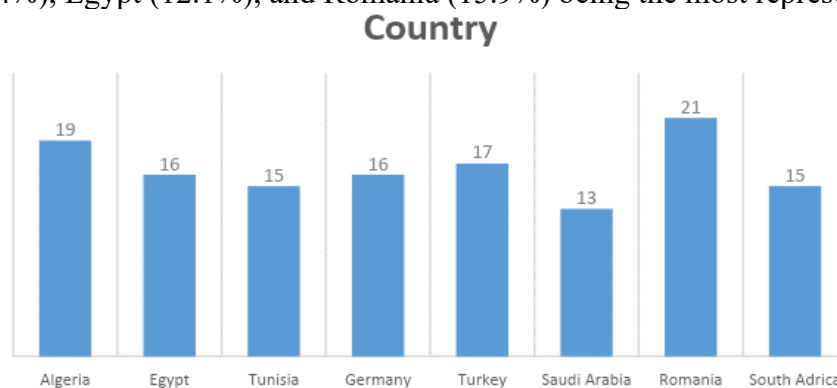


Figure 6. Countries distribution.

3.2.2 Technical Metrics Analysis

The evaluation results reveal varying perceptions among participants regarding the technical metrics of the model. In terms of accuracy, a notable portion (27.3%) strongly agree with the model's accuracy, while 18.9% express disagreement as mentioned in Figure 7. Similarly, for precision, opinions are split, with 13.6% strongly disagreeing and 22.7% strongly agreeing (Figure 8).

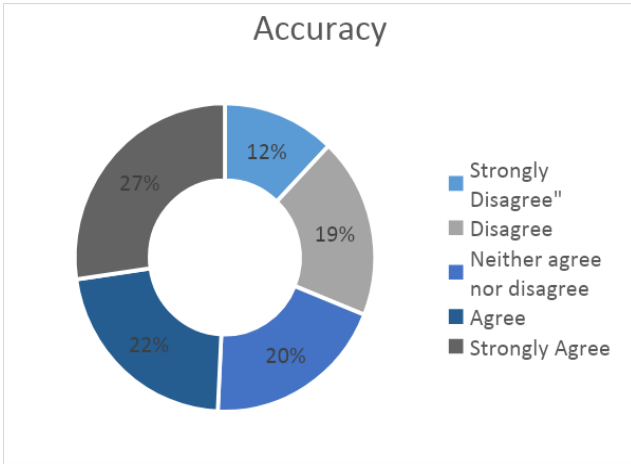


Figure 7. Precision results mean.

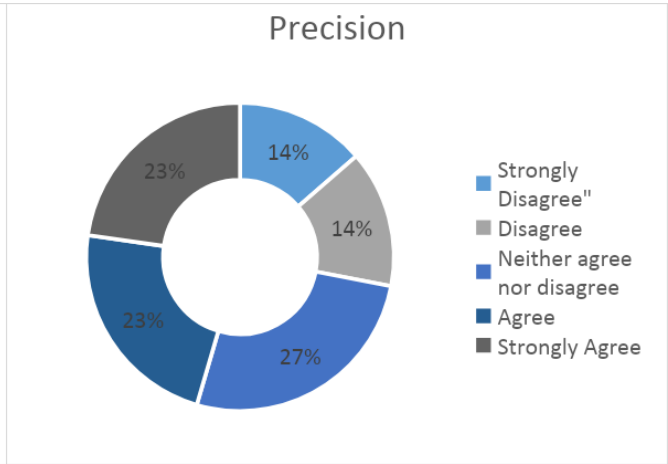


Figure 8. Accuracy results mean.

Regarding recall, there is a divergence of opinions, with 17.4% strongly disagreeing and 17.4% strongly agreeing with the model's recall (Figure 9). Participants also display varied sentiments towards the F1 score, with 20.5% strongly disagreeing and 19.7% strongly agreeing as in Figure 10.

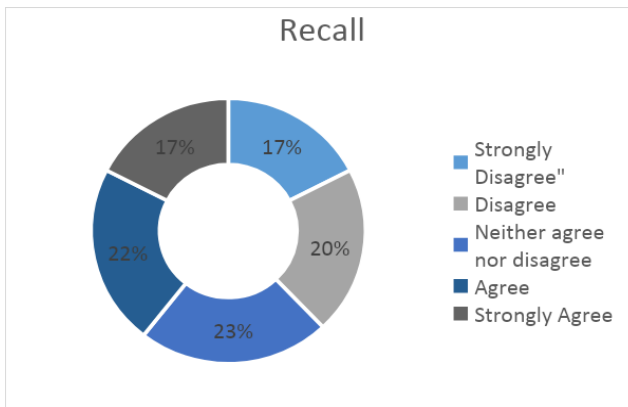


Figure 9. Recall results mean.

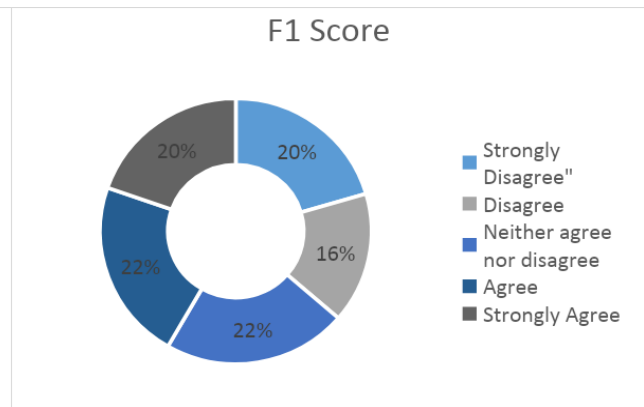


Figure 10. F1 Score results mean.

Regarding the understanding of the confusion matrix, Figure 11 shows that 20.5% strongly disagree, and 22.0% strongly agree. Interpretation of feature importance generates mixed responses, with 19.7% strongly disagreeing and 26.5% strongly agreeing (Figure 12).

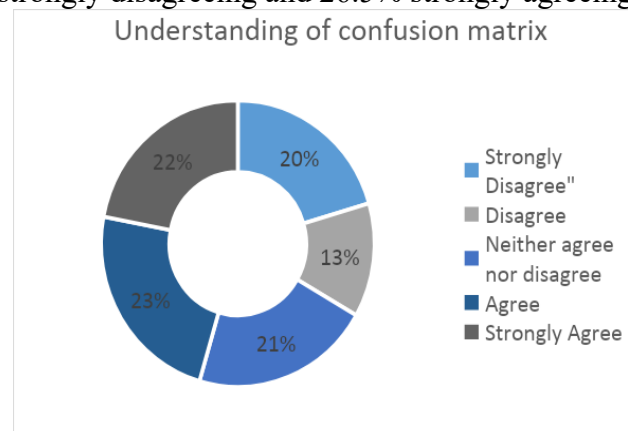


Figure 11. IFI results mean.

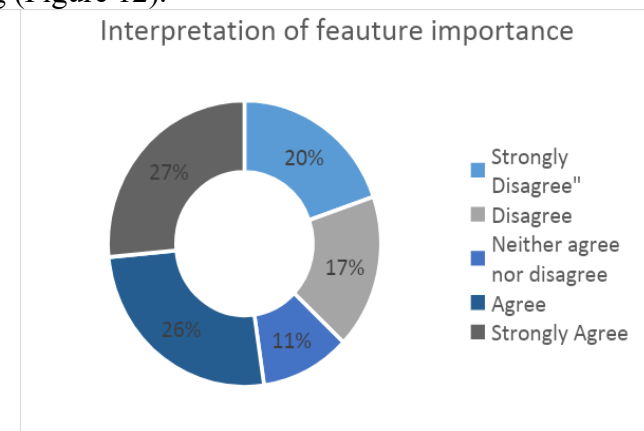


Figure 12. UCM results mean.

These results underscore the nuanced perceptions of participants regarding the model's technical performance, highlighting areas of consensus and divergence.

3.2.3 Urban Metrics Analysis

The assessment of urban metrics unveils a spectrum of perspectives among participants regarding the model's efficacy in identifying specific urban issues. Regarding the detection rate of urban sprawl, Figure 13 shows some opinions diverge, with 25.8% of participants strongly agreeing with the model's capability, while 16.7% strongly disagree (Figure 14).

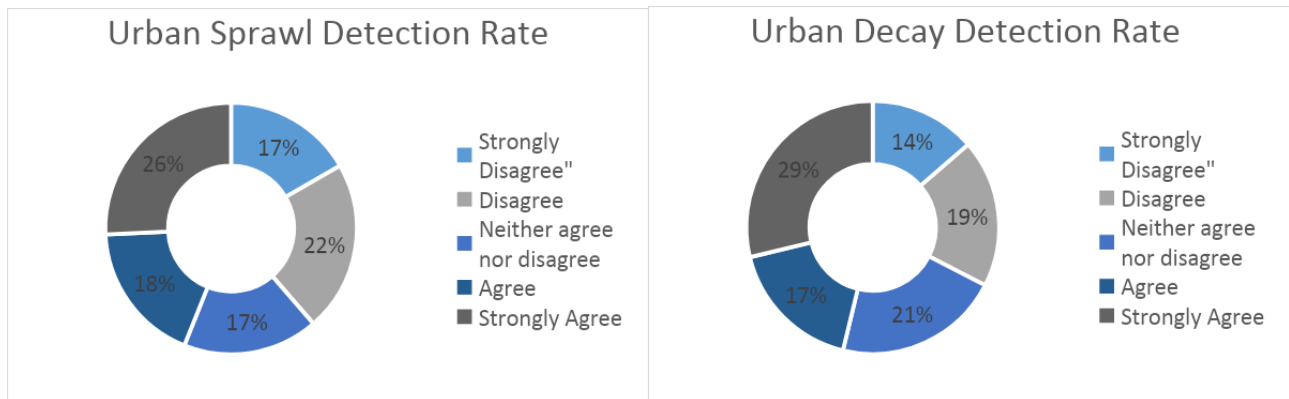


Figure 13. UDDR results mean. **Figure 14.** USDR results mean.

Similarly, for urban decay detection, Figure 15 shows that 28.8% strongly agree, contrasting with 13.6% who strongly disagree. Infrastructure deficiency detection prompts varied responses, with 23.5% disagreeing and 17.4% strongly agreeing. Figure 16 shows the Environmental degradation detection's results which elicits mixed sentiments, as 28.0% disagree and 22.0% strongly agree.

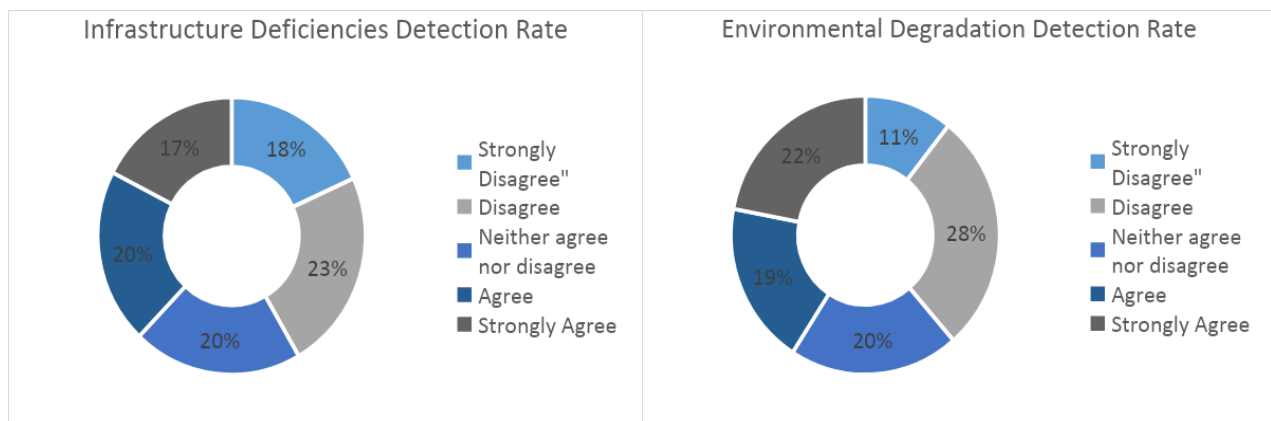


Figure 15. EDDR results mean. **Figure 16.** IDDR results mean.

These results underscore the nuanced perceptions among participants regarding the model's effectiveness in identifying distinct urban challenges.

3.2.4 Statistical Tests

a- Correlations:

Accuracy and F1 Score: There is a significant positive correlation between accuracy and F1 score ($r = 0.216, p < 0.05$), indicating that as accuracy increases, the F1 score tends to increase as well.



Precision and Infrastructure Deficiencies Detection Rate: There is a significant negative correlation between precision and infrastructure deficiencies detection rate ($r = -0.174$, $p < 0.05$), suggesting that higher precision is associated with lower rates of detecting infrastructure deficiencies.

Recall and F1 Score: Recall and F1 score ($r = 0.123$, $p < 0.05$), indicating that higher recall tends to be associated with higher F1 scores.

Understanding of Confusion Matrix and Urban Sprawl Detection Rate: There is a significant negative correlation between understanding of the confusion matrix and urban sprawl detection rate ($r = -0.113$, $p < 0.05$), suggesting that better understanding of the confusion matrix is associated with lower rates of urban sprawl detection.

Interpretation of Feature Importance and Environmental Degradation Detection Rate: There is a significant negative correlation between interpretation of feature importance and environmental degradation detection rate ($r = -0.051$, $p < 0.05$), indicating that better interpretation of feature importance is associated with lower rates of environmental degradation detection.

4. Discussion

4.1 Interpretation of the Model Performance Findings

The model's performance in detecting urban problems, as assessed through the presented prompt and examples, reveals both strengths and areas for improvement.

In Example 01, the model correctly identifies urban sprawl by reasoning about the density of cars parked on the street, indicative of increased population density and limited space for infrastructure development. However, it erroneously identifies the absence of urban decay, infrastructure deficiencies, and environmental degradation based solely on the appearance of a well-maintained street. This suggests that while the model effectively recognizes certain visual cues associated with urban sprawl, it may lack the contextual understanding required to accurately assess other urban problems.

Example 02 demonstrates a similar pattern, with the model correctly identifying urban sprawl based on the presence of cars parked in a commercial or office building's parking lot. However, its assessment of urban decay, infrastructure deficiencies, and environmental degradation appears oversimplified, relying solely on visual cues such as the building's condition and surrounding trees. This highlights the model's tendency to overlook nuanced indicators of urban problems beyond surface-level observations.

In Example 03, the model correctly identifies urban sprawl based on the presence of houses and cars indicating dense population and expansion beyond original boundaries. However, it incorrectly identifies urban decay and infrastructure deficiencies, presuming them based on the density of houses and cars without considering other contextual factors. Nonetheless, the model correctly refrains from identifying environmental degradation due to the absence of clear visual cues in the image.

Overall, while the model demonstrates proficiency in identifying certain urban problems such as urban sprawl, its performance is limited by its reliance on visual cues and its inability to contextualize these cues effectively. To enhance the model's accuracy and effectiveness, future iterations may benefit from incorporating contextual information, semantic understanding, and real-time data integration to provide more nuanced assessments of urban environments.

4.2 Model evaluation

4.2.1 Demographic analysis

The demographic analysis of the model evaluation questionnaire reveals insights into participant characteristics. With a response rate of 66%, the study shows diverse representation across age groups, genders, education levels, and countries of residence. Most participants are aged 25-44, with a relatively balanced gender distribution. The majority hold Bachelor's degrees, and respondents come

from various countries, indicating a broad geographic scope and a diverse pool of perspectives in assessing the urban problems detection model.

4.2.2 Technical Metrics Analysis

The technical metrics analysis showcases diverse perspectives among participants regarding the model's performance. While a significant portion strongly agrees with its accuracy (27.3%) and precision (22.7%), there are notable percentages expressing disagreement. Similarly, opinions on recall and F1 score vary, with some strongly disagreeing (17.4% for each) and others strongly agreeing (also 17.4% for each). Understanding the confusion matrix and interpreting feature importance elicits mixed responses, indicating varying levels of understanding and interpretation among participants. These findings highlight the complexity of evaluating technical metrics and the importance of considering diverse viewpoints in assessing model performance.

4.2.3 Urban Metrics Analysis

The analysis of urban metrics reveals a diverse range of viewpoints among participants regarding the model's ability to identify specific urban issues. While a significant portion strongly agrees with the model's efficacy in detecting urban sprawl (25.8%) and urban decay (28.8%), there are also notable percentages expressing disagreement. Similarly, opinions on infrastructure deficiencies detection and environmental degradation detection are varied, with some disagreeing (23.5% and 28.0%, respectively) and others strongly agreeing (17.4% and 22.0%, respectively).

4.2.4 Correlation interpretation

The correlation analysis (Appendix 01) reveals several significant relationships between different variables:

- Accuracy and F1 Score: There is a positive correlation, suggesting that as accuracy increases, the F1 score tends to increase as well.
- Precision and Infrastructure Deficiencies Detection Rate: A negative correlation indicates that higher precision is associated with lower rates of detecting infrastructure deficiencies.
- Recall and F1 Score: A positive correlation indicates that higher recall tends to be associated with higher F1 scores.
- Understanding of Confusion Matrix and Urban Sprawl Detection Rate: A negative correlation suggests that a better understanding of the confusion matrix is associated with lower rates of urban sprawl detection.
- Interpretation of Feature Importance and Environmental Degradation Detection Rate: Another negative correlation indicates that better interpretation of feature importance is associated with lower rates of environmental degradation detection.

4.2.5 Comparison with previous studies

Our findings were contextualized by discussing the model's performance in relation to existing urban analysis methodologies, such as traditional GIS-based approaches and recent machine learning models. Traditional GIS-based approaches, while providing comprehensive spatial analyses, often lack real-time capabilities and struggle to integrate diverse data types effectively (Yu and Fang, 2023). Recent machine learning models offer advanced pattern recognition and predictive capabilities but are limited by their dependence on large, labelled datasets and susceptibility to biases (Mumuni and Mumuni, 2024; Lepakshi, 2022). In contrast, our model combines real-time data integration and multimodal analysis, offering a more nuanced and dynamic understanding of urban problems. This discussion highlights the added value of our proposed model in providing real-time, data-driven insights for urban planners, effectively addressing the limitations found in both traditional and recent (Šoštarić et al, 2021).

4.2.6 Implications of Enhancing Model Robustness in Urban Planning

The model's reliance on visual cues can be mitigated by incorporating multimodal data sources, such as socio-economic indicators, historical data, and environmental metrics, to provide a more comprehensive analysis of urban problems. Integrating Geographic Information System (GIS) data, real-time sensor data, and textual data from urban reports and social media can enhance contextual understanding and improve the model's accuracy. To address contextual misinterpretations, the AI model could benefit from advanced techniques such as transfer learning and domain adaptation. These approaches would allow the model to leverage pre-trained networks on large datasets and fine-tune them for specific urban contexts. Additionally, incorporating human-in-the-loop feedback mechanisms can help refine the model's predictions by allowing urban planners to provide corrective input and context-specific insights. Biases and fairness issues were addressed by implementing rigorous data preprocessing steps, such as balancing the dataset to represent diverse urban environments and demographic groups. The model's fairness was further evaluated by conducting subgroup analyses to ensure equitable performance across different regions and population segments. Ethical considerations were embedded in the design process to promote transparency, accountability, and inclusivity in urban planning.

Based on the study's findings, several actionable recommendations are proposed for urban planners to enhance their decision-making processes. Firstly, integrating the AI model with existing urban planning tools can significantly improve data-driven decision-making. Utilizing the model's insights allows planners to identify priority areas for infrastructure development and environmental conservation more effectively. Engaging with local communities to validate the model's predictions and gather contextual information is crucial for ensuring the relevance and accuracy of the assessments. Continuously updating the model with new data and feedback will further improve its performance over time. Finally, promoting interdisciplinary collaboration between urban planners, data scientists, and policymakers can leverage the full potential of AI in urban development, ensuring a more comprehensive and informed approach to addressing urban challenges.

5. Conclusion

This study provides a comprehensive synthesis of the performance and perceptions of an urban problems detection model, revealing significant correlations. Notably, there is a positive relationship between accuracy and F1 score ($r = 0.216$, $p < 0.05$) and a negative correlation between precision and infrastructure deficiencies detection rate ($r = -0.174$, $p < 0.05$). These findings highlight areas for improvement in the model's accuracy and precision, offering valuable insights for both academic research and practical applications.

The implications of this research extend to the field of urban planning, where AI-driven decision-making processes can benefit from more accurate and reliable detection models. Practical applications for urban planners include the potential for more informed decision-making processes, leading to better infrastructure development and environmental conservation efforts. Ethical considerations were a core component of this research, with rigorous data preprocessing steps implemented to mitigate biases and ensure fairness. Transparency and accountability were prioritized throughout the design process to promote equitable outcomes in urban planning. Additionally, the findings are generalizable to different urban contexts, provided that the model is adapted to account for local variations and specificities. Future research should explore new areas such as the integration of multimodal data and advanced machine learning techniques to further enhance the model's performance.

Methodological limitations inherent in the research methodology or model architecture may include constraints related to data availability, model complexity, or computational resources, potentially



affecting accuracy and reliability as reported in the study of Aldoseri et al. (2024). The generalizability of findings may be limited by biases or assumptions in the research approach, necessitating careful consideration when interpreting results. Future directions could involve refining the generative model by optimizing hyperparameters or expanding the dataset to encompass a wider range of architectural styles and environmental conditions. Addressing these limitations in future studies is crucial for achieving more effective and equitable urban problem detection.

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Conflicts of Interest

The authors declare no conflicts of interest.

Data availability statement

Additional data related to this study can be obtained from the corresponding author upon request.

Institutional Review Board Statement

Not applicable.

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Appendices

Appendix 1: Correlation table.



Corrélations

	Accuracy	Precision	Recall	F1 Score	Understanding of Confusion Matrix	Interpretation of Feature Importance	Urban Sprawl Detection Rate	Urban Decay Detection Rate	Infrastructure Deficiencies Detection Rate	Environmental Degradation Detection Rate
Accuracy	1									
Corrélation de Pearson		-.040	.014	.216	.139	-.147	.060	.056	-.012	-.013
Sig. (bilatérale)		.646	.876	.013	.111	.093	.493	.521	.890	.887
N	132	132	132	132	132	132	132	132	132	132
Precision		1								
Corrélation de Pearson	-.040		-.053	.018	-.007	-.045	-.056	.081	-.174	-.047
Sig. (bilatérale)	.646		.545	.839	.936	.610	.526	.356	.047	.596
N	132	132	132	132	132	132	132	132	132	132
Recall			1							
Corrélation de Pearson	.014	-.053		.123	-.001	.047	.003	.026	-.049	-.120
Sig. (bilatérale)	.876	.545		.159	.990	.591	.975	.770	.577	.171
N	132	132	132	132	132	132	132	132	132	132
F1 Score				1						
Corrélation de Pearson	.216	.018	.123		.035	.118	.101	-.045	-.054	.045
Sig. (bilatérale)	.013	.839	.159		.694	.179	.248	.609	.538	.605
N	132	132	132	132	132	132	132	132	132	132
Understanding of Confusion Matrix					1					
Corrélation de Pearson	.139	-.007	-.001	.035		-.003	-.113	-.023	.128	.062
Sig. (bilatérale)	.111	.936	.990	.694		.969	.199	.791	.145	.478
N	132	132	132	132	132	132	132	132	132	132
Interpretation of Feature Importance						1				
Corrélation de Pearson	-.147	-.045	.047	.118	-.003		.031	-.034	-.056	.027
Sig. (bilatérale)	.093	.610	.591	.179	.969		.724	.701	.454	.759
N	132	132	132	132	132	132	132	132	132	132
Urban Sprawl Detection Rate							1			
Corrélation de Pearson	.060	-.056	.003	.101	-.113	.031		.006	.088	.081
Sig. (bilatérale)	.493	.526	.975	.248	.199	.724		.948	.315	.356
N	132	132	132	132	132	132	132	132	132	132
Urban Decay Detection Rate								1		
Corrélation de Pearson	.056	.081	.026	-.045	-.023	-.034	.006		-.029	-.029
Sig. (bilatérale)	.521	.356	.770	.609	.791	.701	.948		.744	.740
N	132	132	132	132	132	132	132	132	132	132
Infrastructure Deficiencies Detection Rate									1	
Corrélation de Pearson	-.012	-.174	-.049	-.054	.128	-.056	.088	-.029		-.051
Sig. (bilatérale)	.890	.047	.577	.538	.145	.454	.315	.744		.561
N	132	132	132	132	132	132	132	132	132	132
Environmental Degradation Detection Rate										1
Corrélation de Pearson	-.013	-.047	-.120	.045	.062	.027	.081	-.029	-.051	
Sig. (bilatérale)	.887	.596	.171	.605	.478	.759	.356	.740	.561	
N	132	132	132	132	132	132	132	132	132	132

*. La corrélacion est significative au niveau 0.05 (bilatérale).