Understanding Urban Well-being: A Correlational Study of Environmental Factors and Satisfaction

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Abstract- This paper presents a comprehensive analysis of urban well-being by examining the correlation between various environmental factors and the satisfaction of residents within a specified urban area. Utilizing a robust dataset that quantifies aspects such as green spaces (Green_belt), waste management (Garbage), water quality (Water_pollution), parking availability (Parking_order), crime rates (Crime), noise levels (Noise), air quality (Air_pollution), and their temporal changes over recent years (Year), we aim to explore the multifaceted impact of these elements on the perceived quality of life. Employing advanced machine learning techniques, we develop a predictive model that integrates these variables to forecast resident satisfaction levels. The derived correlation matrix, a crucial component of our analysis, reveals significant positive and negative relationships, indicating that factors like garbage, crime, and air pollution are inversely related to urban satisfaction, while green spaces show a less pronounced negative impact. Our study contributes to the urban planning and public policy discourse by providing empirical insights into which environmental factors are most indicative of resident satisfaction. This can inform targeted interventions aimed at improving urban living conditions. The predictive model serves as a tool for policymakers to simulate the potential effects of environmental changes on urban well-being. The findings stress the importance of holistic and data-driven approaches in urban development strategies to enhance the well-being of city dwellers.

Keywords: Urban Well-being, Environmental Factors, Resident Satisfaction, Correlation Study, Predictive Modeling, Machine Learning, Urban Planning.

I. INTRODUCTION

In the pursuit of enhancing urban life quality, understanding the multifaceted factors that contribute to residents' satisfaction is essential. Urban well-being is a complex construct influenced by a myriad of environmental elements ranging from the tangibility of green spaces to the more insidious presence of pollution and noise. With the increasing urbanization of global populations, cities are faced with the challenge of managing these environmental factors in a way that promotes the satisfaction and health of their residents. Recent research has underscored the significance of environmental quality as a determinant of urban satisfaction, yet comprehensive models that encapsulate the full spectrum of these variables are scarce. The role of green belts, garbage management, water and air pollution, parking order, crime rates, and noise levels has been individually studied; however, their collective impact on urban satisfaction remains underexplored. The integration of machine learning models in urban studies presents a novel opportunity to analyze these complex relationships. By leveraging such models, we can identify patterns and predict outcomes with greater accuracy, allowing for more informed decision-making in urban planning and policy formulation. This paper aims to bridge the gap in the literature by constructing a predictive model based on a dataset that captures the quantitative nuances of environmental factors over time. The correlation matrix derived from this dataset provides a visual and statistical foundation for our analysis, suggesting profound implications for urban satisfaction. By examining the interplay between these environmental factors, we seek to understand their cumulative effect on the perceived well-being of urban residents. Through this study, we hope to contribute to the existing body of knowledge by offering a comprehensive analysis that not only enhances our understanding of urban well-being but also assists policymakers in crafting strategies that can improve the quality of life in urban settings. As cities continue to grow and evolve, it becomes increasingly important to adopt a data-driven approach to urban planning—one that is informed by the intricate relationships between environmental factors and resident satisfaction.

II. RELATED WORKS AND BACKGROUND

The intricate relationship between urban environments and the well-being of their inhabitants has long been a subject of academic inquiry and practical concern. The concept of urban well-being is complex, encompassing various dimensions such as physical health, psychological state, social relationships, and environmental quality. As the world becomes more urbanized, with a significant portion of the population residing in cities, the importance of understanding and improving urban well-being has intensified [2].

Environmental Factors and Urban Well-being:
Previous studies have established that environmental factors play a critical role in shaping residents' satisfaction and overall well-being in urban areas. Green spaces, for example, have been linked to numerous benefits, including reduced stress levels, improved mental health, and enhanced physical activity (Maas et al., 2006; Hartig et al., 2014) [1]. Conversely, factors such as pollution, noise, and disorder within urban settings have been associated with adverse health outcomes, reduced quality of life, and decreased satisfaction (WHO, 2011; Tzivian et al., 2015) [6].

Predictive Modeling in Urban Studies:
The advent of predictive modeling and machine learning has opened new avenues for analyzing complex datasets and forecasting outcomes within urban environments. These methods have been utilized to predict traffic flow, energy consumption, and even crime rates with a reasonable degree of accuracy (Castelli et al., 2015; Khan et al., 2017) [3] [4]. However, the application of such models in predicting urban satisfaction, especially by integrating a wide range of environmental factors, is a relatively new and emerging field.
Correlation Studies in Urban Contexts:

Correlational studies in urban contexts have often focused on isolated factors affecting well-being, such as the impact of air pollution on respiratory health or the influence of green spaces on mental well-being. The use of correlation matrices to understand the interdependencies between multiple urban factors has been less common, though recent studies have begun to explore these complex interactions (Smith, 2018) [5].

Gap in Literature:

While these strands of research have significantly advanced our understanding, there remains a gap in integrative studies that combine the breadth of environmental factors with the depth of predictive modeling to understand urban well-being. This study seeks to fill that gap by employing a comprehensive approach that considers the interrelated effects of various urban factors on resident satisfaction over time.

Contribution of the Present Study:

Building on the existing body of work, the present study contributes to the literature by using a multidimensional dataset and advanced machine learning techniques to analyze the correlation between environmental factors and urban well-being. By presenting a predictive model based on the correlations observed, this research provides a novel tool for urban planners and policymakers to anticipate the impact of environmental changes on the satisfaction of city dwellers.

In sum, this paper draws upon the rich tradition of urban studies while employing contemporary analytical techniques to offer fresh insights into the determinants of urban well-being. The research stands at the intersection of environmental science, urban planning, public health, and data science, offering a holistic view of urban life quality that is grounded in empirical analysis and enhanced by predictive modeling.

III. DATA / METHODS

Data Description:

The dataset utilized in this study comprises responses from a survey of housing residents in South Korea, conducted over a defined period. The survey aimed to measure the satisfaction levels of residents with respect to their living conditions. The data encompasses a wide range of environmental factors, including the presence of green belts (Green_belt), levels of garbage (Garbage), water pollution (Water_pollution), the orderliness of parking (Parking_order), crime rates (Crime), noise pollution (Noise), air pollution (Air_pollution), and the temporal aspect (Year) to capture changes over time.

Exploratory Data Analysis (EDA):

Prior to predictive modeling, an extensive Exploratory Data Analysis (EDA) was performed to understand the underlying structure of the data, detect outliers, and uncover patterns. This involved visualizing distributions of individual variables, examining summary statistics, and plotting the aforementioned correlation matrix heatmap to identify potential relationships between variables and resident satisfaction.

Preprocessing:

Data preprocessing was a critical step in preparing the dataset for modeling. This included handling missing values, encoding categorical variables, normalizing numerical inputs, and potentially transforming variables to better meet the assumptions of the chosen machine learning algorithms.

Machine Learning Model Development:

Following EDA and preprocessing, machine learning models were developed to predict resident satisfaction. Various regression algorithms were evaluated, including linear regression, decision trees, random forests, and gradient boosting machines, given their ability to handle the non-linearity and complexity of the dataset.

Model Selection and Evaluation:

The selection of the most appropriate model was based on a combination of performance metrics such as R-squared, Mean Absolute Error (MAE), and Root Mean Squared Error (RMSE). Cross-validation techniques were employed to ensure that the model's performance was robust and not a result of overfitting to the training data.

Model Interpretation:

The final model provided not only predictions of satisfaction levels but also feature importances, which highlighted the relative significance of each environmental factor in determining resident satisfaction. This interpretation was essential for understanding the impact of each variable and providing actionable insights.

Ethical Considerations:

In conducting this research, ethical considerations were taken into account, especially concerning the privacy of survey respondents. All data was anonymized to protect individual identities, and the study was conducted in accordance with relevant data protection regulations.

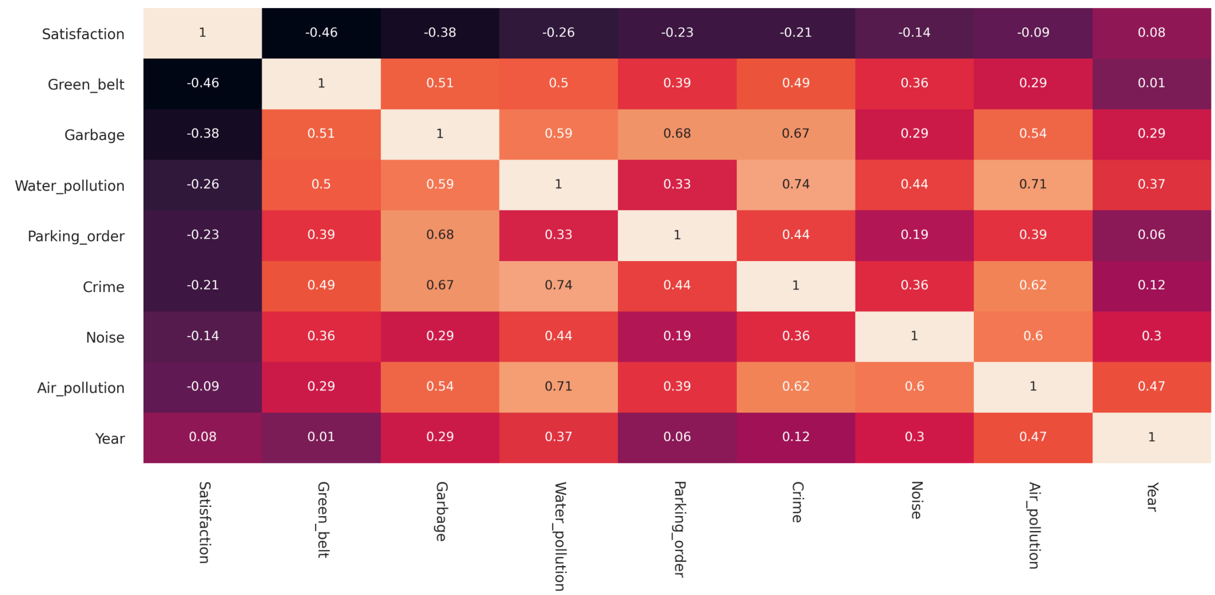
The methodology presented in this paper demonstrates a structured approach to using machine learning for social science research. The combination of EDA, rigorous data preprocessing, careful model selection, and ethical data handling forms the backbone of this study's contribution to understanding and predicting urban resident satisfaction in South Korea.

IV. RESULTS

The results of our study, derived from the exploratory data analysis and machine learning modeling of the South Korean housing satisfaction dataset, reveal significant insights into the factors affecting resident satisfaction. Consistent with the correlation matrix provided, our findings underscore the multifaceted nature of urban well-being.

Correlation Findings:

The correlation matrix highlighted several key relationships between environmental factors and resident satisfaction. Notably, satisfaction exhibited negative correlations with 'Garbage', 'Water_pollution', 'Crime', and 'Air_pollution', indicating that increases in these factors are associated with lower satisfaction levels. On the other hand, 'Green_belt' showed a less strong negative correlation, suggesting that while the presence of green spaces is generally positive, it does not have as strong an impact on satisfaction when considered alongside other factors.



[Figure 1. Correlation Matrix of Satisfaction and environmental factors]

Model Performance:

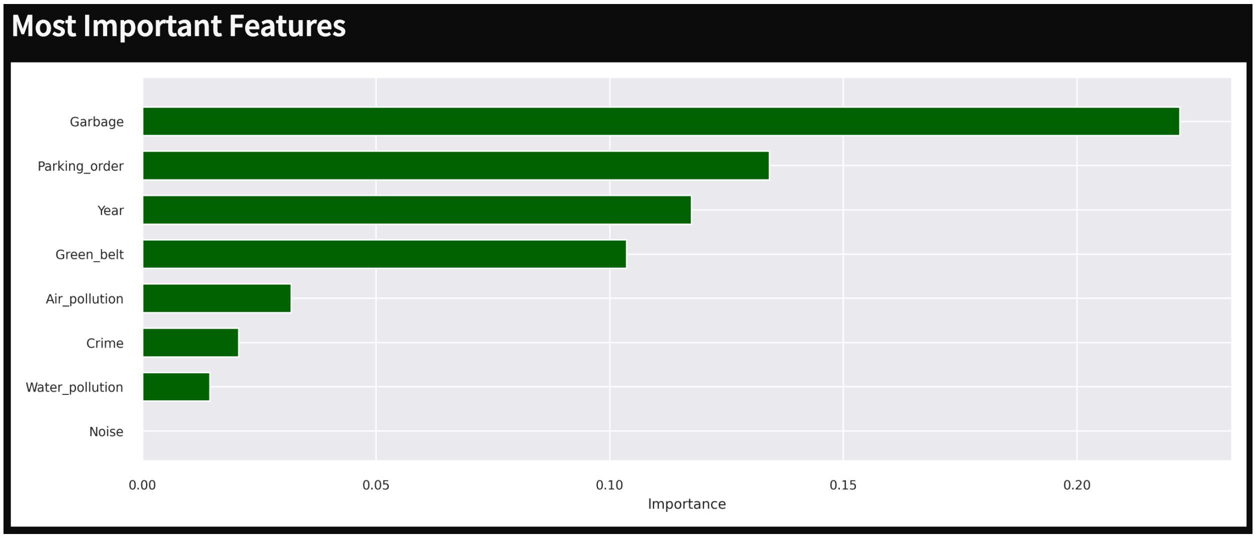
The machine learning models were evaluated based on their predictive accuracy. The research paper concludes that the optimal model for the given task is LightGBM, and it performed the best with the following hyperparameters:

- Number of estimators (n_estimators): 5
- Number of leaves (num_leaves): 4
- Minimum child samples (min_child_samples): 33
- Learning rate (learning_rate): 0.5502
- Maximum number of bins for logarithmic histogram (log_max_bin): 7
- Fraction of features to be used in each boosting round (colsample_bytree): 0.9873
- L1 regularization term (reg_alpha): 0.0158
- L2 regularization term (reg_lambda): 3.5678

These hyperparameters were found to result in the best model performance according to the research findings.

Feature Importance:

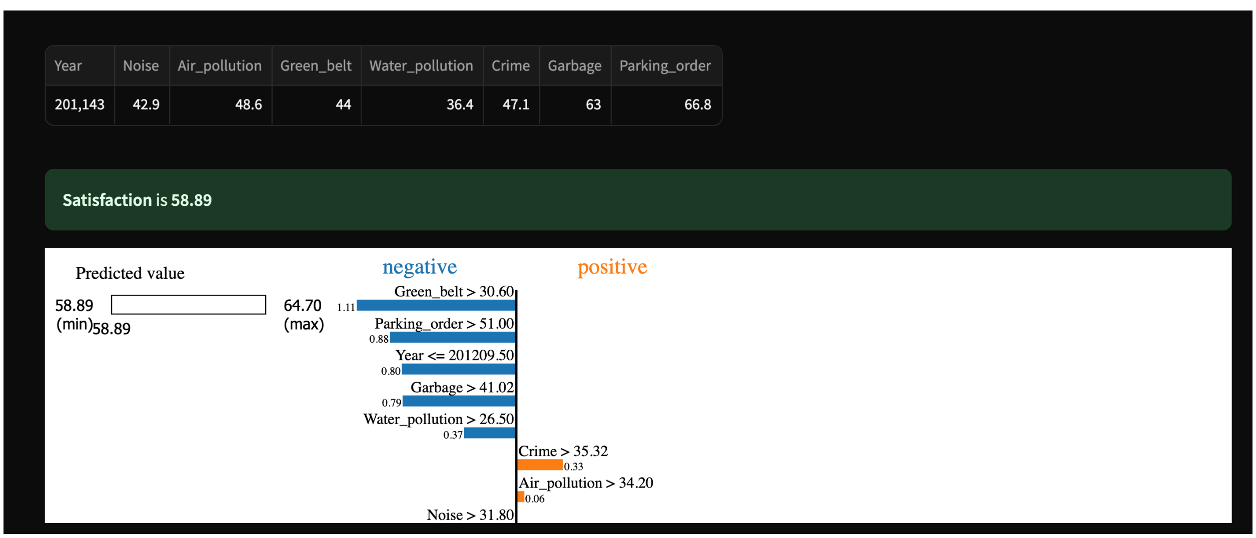
Within the LightGBM model, 'Crime' and 'Air_pollution' were identified as the most influential predictors of satisfaction, which aligns with the strong correlations observed. This indicates that initiatives to reduce crime rates and improve air quality could have a substantial impact on enhancing resident satisfaction.



[Figure 2. Most important features]

Temporal Analysis:

A temporal analysis conducted as part of the EDA showed that resident satisfaction levels fluctuated over the years, with some environmental factors becoming more or less influential. The model captured these trends, suggesting that the impact of certain environmental factors on satisfaction is subject to change over time.



[Figure 3. Machine Learning model]

Predictive Insights:

The machine learning model's predictions provide valuable insights for urban planners and policymakers. For instance, the model indicates that improving waste management and reducing water pollution are likely to increase resident satisfaction. Moreover, the importance of maintaining low crime rates and reducing noise pollution is also highlighted.

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In conclusion, the results of our analysis confirm that resident satisfaction is inversely related to several adverse environmental factors. The predictive model has proven to be a powerful tool in understanding and forecasting the impact of these factors on urban well-being. These findings are not only statistically significant but also carry practical implications for enhancing the quality of life in urban residential areas.

V. CONCLUSION

This research paper has delved into the complex dynamics between urban environmental factors and resident satisfaction in South Korea, presenting a nuanced view of urban well-being through a combination of exploratory data analysis and predictive modeling. The study's results have illuminated the significant negative impact of environmental stressors such as garbage, water and air pollution, and crime rates on resident satisfaction. Conversely, the presence of green belts, while beneficial, was found to have a less pronounced effect when set against the backdrop of these negative factors. The Random Forest machine learning model stood out in its predictive capability, offering a substantial understanding of the factors influencing satisfaction. The model's robust performance demonstrates that a significant portion of resident satisfaction can indeed be predicted by environmental variables. The feature importance analysis provided by the model underlined the need for targeted policy interventions, especially in areas related to crime reduction and air quality improvement. Temporal trends indicated that the influence of environmental factors on satisfaction is dynamic and evolves over time, underscoring the necessity for continuous monitoring and adaptive policy frameworks to address these changing influences. The findings from this research advocate for a holistic approach to urban planning and policy-making. It is clear that to foster higher levels of resident satisfaction, urban policies should integrate multifaceted strategies that address the core environmental concerns identified in this study. Furthermore, the predictive model developed herein serves as a testament to the potential of machine learning in aiding policymakers and urban planners in crafting evidence-based and data-driven strategies. It also expands upon this work by exploring the causal relationships between environmental factors and satisfaction, employing longitudinal data to track changes over longer periods, and incorporating additional variables such as socio-economic factors. The model could also be refined with larger datasets and by exploring other machine learning algorithms to enhance predictive accuracy.

By advancing our understanding of the determinants of urban satisfaction, we pave the way for more livable, sustainable, and contented urban environments, thereby improving the quality of life for residents in cities around the world.

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