Indonesian Journal of Artificial Intelligence and Data Mining (IJAIDM)
Vol. 7, No. 1, March 2024, pp. 167 – 173
p-ISSN: 2614-3372 | e-ISSN: 2614-6150

Predicting Urban Happiness: A Comparative Analysis of Deep Learning Models

Gregorius Airlangga
Information System Study Program, Atma Jaya Catholic University of Indonesia
Email: gregorius.airlangga@atmajaya.ac.id

Article Info

Article history:
Received Dec 22th, 2023
Revised Feb 20th, 2024
Accepted Mar 30th, 2024

Keyword:
CNN
Comparison
Deep Learning
LSTM
Urban Happiness

ABSTRACT

This study explores the efficacy of various deep learning models in predicting urban happiness scores, a critical indicator of the quality of life in urban environments. Recognizing the complex interplay of factors contributing to urban happiness, we employed a suite of models, including Dense Neural Networks (DNN), Long Short-Term Memory networks (LSTM), Convolutional Neural Networks (CNN), Autoencoders, Multi-Layer Perceptron with Dropout (MLP Dropout), and Simple Recurrent Neural Networks (RNN), to analyze a comprehensive dataset encompassing environmental quality, socio-economic factors, and urban infrastructure. Our methodology centered on rigorous data preprocessing to ensure integrity and usability, followed by a detailed comparative analysis of model performances based on Root Mean Squared Error (RMSE) metrics. The results revealed that the CNN model outperformed others in identifying spatial patterns crucial for urban happiness, indicating its superior capability in processing complex urban data. In contrast, the LSTM model showed less accuracy, suggesting a nuanced understanding of temporal data's role in predicting urban happiness. This research not only sheds light on the potential of deep learning in urban studies but also offers valuable insights for urban planners and policymakers aiming to enhance urban living conditions. Through this comparative analysis, our study contributes to the growing discourse on leveraging advanced data analytics for urban planning and opens avenues for future research into the integration of diverse data sources and model hybridization to refine urban happiness predictions.

Corresponding Author:
Gregorius Airlangga,
Information System Study Program,
Atma Jaya Catholic University of Indonesia,
Jakarta, Indonesia
Email: gregorius.airlangga@atmajaya.ac.id

DOI: http://dx.doi.org/10.24014/ijaidm.v7i1.28801

1. INTRODUCTION

In the quest to enhance urban living and make cities more livable, the subjective well-being or happiness of urban residents has gained prominence as a pivotal metric for urban planners and policymakers [1]–[3]. The pursuit of happiness, a fundamental human goal, is significantly influenced by one's living environment, making the study of urban happiness a critical area of research within urban studies, environmental psychology, and data science [4]–[6]. The integration of artificial intelligence (AI) and machine learning (ML) techniques in urban studies offers unprecedented opportunities to understand and predict patterns of happiness across urban landscapes [7]–[10]. This research leverages deep learning models to forecast happiness scores in cities, considering a wide array of factors including environmental quality, socio-economic conditions, and urban infrastructure [11]–[13]. The academic exploration of happiness within urban contexts is multifaceted, examining how various factors such as green spaces, air and noise pollution, traffic conditions, and access to healthcare and other services contribute to well-being [14]–[16]. Studies have historically utilized statistical models to evaluate these relationships, with recent advancements in computational power and data availability ushering in the era of machine learning and deep learning models [17]–[19]. These models offer nuanced insights into the complex, non-linear relationships between urban environments and resident happiness. Research has progressively embraced sophisticated neural network architectures, such as Dense Neural Networks (DNNs) [20], Long Short-Term Memory (LSTM) networks [21], Convolutional Neural Networks (CNNs) [22], and Autoencoders [23], to analyze urban data. However, there remains a significant gap in applying these advanced models comprehensively to predict urban happiness, particularly in combining multiple urban variables into a unified analysis framework.

The urgency of this research is underscored by the global trend of rapid urbanization, with a growing proportion of the world's population residing in urban areas [24]–[26]. This demographic shift intensifies the challenges and complexities of urban living, making the pursuit of urban happiness more critical than ever. The current state-of-the-art in urban happiness research employs deep learning to unearth patterns and predictors of happiness with greater accuracy than traditional models [11], [27], [28]. These advanced models have demonstrated their potential in various domains, including emotion recognition, traffic prediction, and environmental monitoring, showcasing their versatility and power in handling complex datasets [29]–[31]. This study aims to fill the existing research gap by applying a comprehensive suite of deep learning models to predict urban happiness scores. While previous studies have explored individual aspects of urban living or applied machine learning models in isolation, there is a lack of comprehensive research that utilizes a wide array of deep learning architectures to analyze the multifaceted nature of urban happiness [32]–[34]. Our goal is to systematically compare the performance of various deep learning models, including but not limited to DNNs, LSTM, CNN, Autoencoders, MLP with Dropout, and Simple RNN, in predicting happiness scores based on diverse urban variables.

This research makes several contributions to the fields of urban studies and data science. Firstly, it provides a comparative analysis of multiple deep learning models, offering insights into their predictive capabilities and applicability to urban happiness prediction. Secondly, by employing a rich dataset encompassing a broad spectrum of urban factors, this study unveils complex relationships between urban attributes and happiness, highlighting the potential of deep learning in uncovering subtle patterns within urban data. Thirdly, this work advances methodological approaches in urban studies, showcasing the integration of AI and ML techniques to address urban challenges. Finally, the findings of this study are poised to offer practical guidance for urban planners and policymakers, informing strategies to enhance urban living conditions and thereby improve the well-being of city dwellers. The structure of the journal article is meticulously designed to guide the reader through the comprehensive exploration of utilizing deep learning techniques to predict urban happiness. The article is organized into distinct sections, each serving a pivotal role in unfolding the research narrative and presenting the findings.

In the section three, we explain a research methodology that lays the foundation of the research design, detailing the meticulous process of data collection, preprocessing, and the selection of deep learning models. This section is pivotal in elucidating the rigorous approach adopted to ensure the reliability and validity of the study. Each deep learning model employed is described with precision, shedding light on their architecture and the rationale behind their selection. Furthermore, this section discusses the metrics chosen for evaluating the performance of these models, providing a clear understanding of the criteria used to assess their effectiveness in predicting urban happiness. The methodology section is crucial for replicability and transparency, allowing readers to comprehend the thoroughness of the research process.

On the next section, we explain Results and Discussion unveils the outcomes of the comparative analysis of deep learning models, marking a significant milestone in the research journey. This section is where the data comes to life, revealing the capabilities of each model in predicting urban happiness. The discussion extends beyond mere statistical outcomes to interpret the results within the broader context of urban planning and happiness. It critically examines the implications of the findings, contemplating how they can inform strategies to enhance urban environments and improve the well-being of city dwellers. This section is instrumental in bridging the gap between theoretical research and practical applications, offering insights that could potentially shape future urban policies and planning practices. Lastly, we explain conclusions, it serves as the culmination of the research endeavor, summarizing the key findings and reflecting on the study's limitations. This introspective section not only acknowledges the constraints of the research but also proposes avenues for future investigations, suggesting how subsequent studies could build upon the findings of the current study. Moreover, it considers the broader implications of applying deep learning in urban studies, pondering the potential of these advanced technologies to revolutionize urban planning and policy formulation. The conclusion underscores the significance of the research, reinforcing its contributions to the fields of urban studies and data science.

2. RESEARCH METHOD

2.1. Data Collection

The dataset central to this study was meticulously compiled from various urban indicators, focusing on factors identified in literature as influential to urban happiness. The data can be downloaded from [35]. These indicators include environmental quality (Air Quality Index, Green Space Area), socio-economic factors (Cost of Living Index, Healthcare Index), and urban living conditions (Traffic Density, Decibel Level). The data was sourced from publicly available urban datasets and aggregated for cities worldwide, ensuring a diverse and comprehensive dataset. This collection process aimed to gather a balanced representation of urban environments to generalize the findings across different urban settings.

2.2. Data Preprocessing

Given the heterogeneous nature of the collected data, a rigorous preprocessing routine was implemented. This process began with the integration of the training and test datasets, followed by the removal of duplicate entries to maintain data integrity. Subsequently, the dataset was filtered to include only records with a positive Happiness Score, ensuring the focus remained on meaningful urban happiness indicators. The preprocessing phase also involved the transformation of categorical variables into a machine-readable format. Notably, categorical columns identified during the initial analysis were encoded using OneHotEncoder, allowing the models to process non-numeric data effectively. This encoding step was crucial for incorporating qualitative indicators such as month and year into the analysis. Related to the categorical variables, such as month and year, identified during the initial analysis were encoded using the OneHotEncoder as presented in the equation (1). This encoding transformed categorical variables into a machine-readable format, allowing the models to process non-numeric data effectively. Additionally, data normalization was conducted using the StandardScaler as presented in the equation (2) to ensure that all features contributed equally to the model's learning process, mitigating the risk of bias towards variables with higher magnitude.

$$\boldsymbol{X_{encoded}} = \text{OneHotEncoder}\left(\boldsymbol{X_{categorical}}\right) \quad (1)$$

Where X_{encoded} represents the matrix of encoded features, and $X_{\text{categorical}}$ represents the matrix of categorical features before encoding.

$$\boldsymbol{X_{normalized}} = \frac{\boldsymbol{X} - \mu}{\sigma} \quad (2)$$

Where X represents the feature matrix before normalization, μ is the mean of each feature, and σ is the standard deviation of each feature.

2.3. Model Development

This research employed a suite of deep learning models to predict urban happiness scores, each chosen for their unique capabilities in handling sequential, spatial, or complex patterned data. The models developed include Dense Neural Network (DNN), Long Short-Term Memory (LSTM), Convolutional Neural Network (CNN), Autoencoder, Multi-Layer Perceptron (MLP) and Recurrent Neural Network (RNN). DNN is a sequential model comprising layers with 128, 64, and 1 neuron(s), respectively, each followed by a ReLU activation as presented in the equation (3), except for the output layer. This model was designed to capture the non-linear relationships between urban indicators and happiness scores.

LSTM is tailored for sequential data processing, this model featured LSTM layers followed by dense layers, catering to the temporal aspects of the data, such as trends over months or years. Furthermore, we use CNN in order to identifying spatial patterns, this model was structured with convolutional and max-pooling layers, followed by a flattening layer and dense layers, aiming to detect patterns across different urban factors. Furthermore, Autoencoder is deployed for its ability to reduce dimensionality and capture the intrinsic structure of the data, the autoencoder model comprised an encoder to compress data and a decoder to reconstruct it, followed by a regression layer for prediction. In addition, we use MLP Dropout as presented in the equation (4) that have incorporated dropout layers to prevent overfitting, ensuring the model's generalizability across unseen data. Then, we use SimpleRNN layers, this model aimed to capture sequential dependencies and patterns within the data, pertinent for analyzing temporal urban data. Each model was compiled with the Adam optimizer as presented in the equation (5) – (9) and mean squared error loss function as presented in the equation (10), reflecting the regression nature of the task.

$$\text{ReLU}(x) = \max(0, x) \quad (3)$$

$$\text{Dropout}(x) = x \cdot \text{Bernoulli}(p) \tag{4}$$

$$m_t = \beta_1 m_{t-1} + (1 - \beta_1) g_t \tag{5}$$

$$v_t = \beta_2 v_{t-1} + (1 - \beta_2) g_t^2 \tag{6}$$

$$\widehat{m_t} = \frac{m_t}{1 - \beta_1^t} \tag{7}$$

$$\widehat{v_t} = \frac{v_t}{1 - \beta_2^t} \tag{8}$$

$$\theta_{t+1} = \theta_t - \frac{\eta \cdot \widehat{m_t}}{\sqrt{\widehat{v_t}} + \epsilon} \tag{9}$$

$$\text{MSE} = \frac{1}{n}\sum_{i=1}^{n}(y_i - \widehat{y_i})^2 \tag{10}$$

2.4. Model Evaluation

Model performance was evaluated using the Root Mean Squared Error (RMSE) metric as presented in the equation (11), which quantifies the difference between the predicted happiness scores and the actual scores. This metric was chosen for its sensitivity to large errors, ensuring the models' accuracy in predicting urban happiness. The training process involved splitting the dataset into training and test sets, with 50% of the data allocated for testing to assess the models' performance on unseen data. This split, coupled with the evaluation metric, facilitated a comprehensive assessment of each model's predictive capability, laying the groundwork for identifying the most effective model(s) for predicting urban happiness.

$$\text{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \widehat{y_i})^2} \tag{11}$$

3. RESULTS AND ANALYSIS

In this section, it is explained the results of research and at the same time is given the comprehensive discussion. Results is presented in the table 1. The CNN model emerged as the most accurate in predicting urban happiness scores, with an RMSE of 0.5728. This superior performance can be attributed to the CNN's ability to extract and learn the most relevant features from the urban data, which likely contains spatial patterns that are pivotal in determining urban happiness. This finding underscores the potential of CNNs in handling complex, multi-dimensional data, a characteristic often found in urban datasets.

The RNN and Dense models also demonstrated commendable performance, with RMSEs of 0.7429 and 0.7829, respectively. The RNN model's success can be linked to its proficiency in capturing sequential dependencies within the data, suggesting that temporal factors play a significant role in urban happiness. Meanwhile, the Dense model's relatively low RMSE highlights the effectiveness of fully connected layers in understanding the relationships between different urban factors and happiness. Conversely, the LSTM model recorded the highest RMSE of 1.2038, indicating challenges in modeling urban happiness scores accurately. This outcome might reflect the LSTM's sensitivity to the quality of temporal sequences within the dataset or its complexity in capturing the dynamics of urban happiness. It suggests that not all sequential data models are equally suited for every dataset or problem type, emphasizing the need for model selection based on the specific characteristics of the data and task.

The Autoencoder and MLP Dropout models yielded RMSE values of 0.9179 and 0.9364, respectively. While not as accurate as the CNN or RNN models, these results highlight the utility of these models in understanding and predicting urban happiness to a certain extent. The Autoencoder's performance, in particular, suggests that dimensionality reduction and feature learning play a role in capturing the essence of urban happiness, albeit less effectively than direct prediction models like CNNs. The MLP Dropout model's performance, near that of the Autoencoder, indicates that addressing overfitting through dropout layers does not necessarily compensate for the model's inherent limitations in capturing the complex interplay of factors influencing urban happiness. The findings from this study offer several implications for urban studies and the application of deep learning in predicting urban happiness. The superior performance of the CNN model illuminates the critical role of spatial patterns in urban data, suggesting that models capable of extracting such patterns are more likely to succeed in predicting urban happiness. This insight can guide urban planners and policymakers in focusing on spatially relevant urban factors, such as green spaces, traffic congestion, and infrastructure layout, when aiming to enhance urban happiness.

The varying performance of the models also highlights the importance of model selection in urban studies. It underscores that the choice of model should be informed by the data's nature and the specific urban phenomenon being studied. For instance, when dealing with data that has a strong temporal component, RNNs might be more appropriate, while CNNs could be better suited for data with pronounced spatial patterns. Furthermore, the relatively higher RMSE of the LSTM model suggests the need for further investigation into the model's configuration and the temporal dynamics of the data. It may also indicate the potential for combining models or using hybrid approaches to better capture the complexities of urban happiness. This study's exploration of deep learning models in predicting urban happiness scores reveals significant insights into the potential and limitations of various neural network architectures for urban studies. The CNN model's standout performance underscores the value of spatial feature extraction in understanding urban happiness. Meanwhile, the results collectively emphasize the necessity of careful model selection based on the specific attributes and challenges of urban data. These findings not only contribute to the academic discourse on urban happiness but also offer practical guidance for leveraging deep learning in urban planning and policy-making to foster happier urban environments.

Table 1. The performance of Deep Learning Algorithms

Method	RMSE
Dense Model	0.7828726742688900
LSTM	1.2037781813100201
MLP with Dropout	0.9363827225020532
Autoencoder	0.9178949422567036
RNN	0.7429113630776178
CNN	0.5727550578433185

4. CONCLUSION

This research embarked on an exploratory journey with the primary objective of harnessing the power of deep learning models to predict urban happiness scores. Motivated by the critical role urban environments play in influencing the well-being of their inhabitants, our study sought to identify the most effective deep learning model for capturing the complex dynamics that contribute to urban happiness. By conducting a comparative analysis of six models—Recurrent Neural Network (RNN), Autoencoder, Multi-Layer Perceptron with Dropout (MLP Dropout), Dense Neural Network (DNN), Convolutional Neural Network (CNN), and Long Short-Term Memory (LSTM)—we aimed to bridge the gap between the theoretical potential of deep learning and its practical application in urban studies. Reflecting on our objectives, this study not only adhered to its aim of evaluating multiple deep learning models but also illuminated the nuanced importance of model selection based on the characteristics of urban data. The analysis revealed a notable variance in model performance, with the CNN model emerging as the most adept, particularly in extracting spatial patterns critical for predicting urban happiness. This outcome underscores the significance of spatial considerations in urban happiness and supports the initial premise that understanding and leveraging these spatial factors are paramount for enhancing urban well-being.

The superior performance of the CNN model, followed by the RNN and DNN models, validates our approach and methodology, demonstrating that certain models, due to their intrinsic capabilities, are more suited for analyzing specific types of data. This finding directly contributes to our objective of identifying effective models for urban happiness prediction and highlights the critical role of spatial patterns. Conversely, the higher RMSE associated with the LSTM model suggests a misalignment with the temporal aspects of the urban happiness data, providing a valuable lesson on the importance of aligning model strengths with data characteristics—a core consideration of our research objectives. This research's contribution extends beyond model comparison, offering practical insights for urban planners and policymakers on the importance of spatial factors in urban design. By reaffirming the necessity for careful model selection tailored to the data's unique attributes, our study enriches the field of urban analytics, paving the way for more nuanced and effective applications of deep learning in urban planning and policy-making. Looking forward, the research opens avenues for further exploration, including the integration of a wider array of urban factors, the examination of hybrid models, and the direct application of these insights to targeted urban interventions. Through this work, we have laid a foundational step towards realizing the full potential of deep learning in deciphering the complexities of urban happiness, aligning with our initial objectives and setting the stage for future advancements in urban analytics.

REFERENCES

[1] J. Pykett, “Spatialising happiness economics: Global metrics, urban politics, and embodied technologies,” Trans. Inst. Br. Geogr., vol. 47, no. 3, pp. 635–650, 2022.

[2] M. A. Nanor, M. Poku-Boansi, and K. K. Adarkwa, “Determinants of subjective wellbeing in rural communities: Evidence from the Juaben Municipality, Ghana,” Cities, vol. 113, p. 103140, 2021.

[3] N. Biloria, “From smart to empathic cities,” Front. Archit. Res., vol. 10, no. 1, pp. 3–16, 2021.

[4] L. Kang, Z. Yang, and F. Han, “The impact of urban recreation environment on residents’ happiness—based on a case study in China,” Sustainability, vol. 13, no. 10, p. 5549, 2021.

[5] S. D. Luca, “Preferring or Needing Cities?(Evolutionary) psychology, utility and life satisfaction of urban living,” City, Cult. Soc., vol. 24, p. 100375, 2021.

[6] M. W. Mehaffy, “Health and happiness in the new urban agenda: The central role of public space,” Sustainability, vol. 13, no. 11, p. 5891, 2021.

[7] T. Yigitcanlar et al., “Artificial intelligence technologies and related urban planning and development concepts: How are they perceived and utilized in Australia?,” J. Open Innov. Technol. Mark. Complex., vol. 6, no. 4, p. 187, 2020.

[8] M. Burry, “A new agenda for AI-based urban design and planning,” in Artificial Intelligence in Urban Planning and Design, Elsevier, 2022, pp. 3–20.

[9] W. U. Jun, “The Fourth Paradigm: A Research for the Predictive Model of Livability Based on Machine Learning for Smart City in The Netherlands,” Landsc. Archit., vol. 27, no. 5, pp. 11–29, 2020.

[10] Y. Huang et al., “GIS-Based Emotional Computing: A Review of Quantitative Approaches to Measure the Emotion Layer of Human--Environment Relationships,” ISPRS Int. J. Geo-Information, vol. 9, no. 9, p. 551, 2020.

[11] R. Jaiswal and S. Gupta, “Money talks, happiness walks: dissecting the secrets of global bliss with machine learning,” J. Chinese Econ. Bus. Stud., pp. 1–48, 2023.

[12] U. Ependi, A. F. Rochim, and A. Wibowo, “An Assessment Model for Sustainable Cities Using Crowdsourced Data Based on General System Theory: A Design Science Methodology Approach,” Smart Cities, vol. 6, no. 6, pp. 3032–3059, 2023.

[13] A. Manimuthu, V. Dharshini, I. Zografopoulos, M. K. Priyan, and C. Konstantinou, “Contactless technologies for smart cities: big data, IoT, and cloud infrastructures,” SN Comput. Sci., vol. 2, no. 4, p. 334, 2021.

[14] M. S. Syamili, T. Takala, A. Korrensalo, and E.-S. Tuittila, “Happiness in urban green spaces: A systematic literature review,” Urban For. \& Urban Green., p. 128042, 2023.

[15] N. Karimi, H. Sajadzadeh, and F. Aram, “Investigating the Association between Environmental Quality Characteristics and Mental Well-Being in Public Open Spaces,” Urban Sci., vol. 6, no. 1, p. 20, 2022.

[16] H. Zhu, L. Shen, and Y. Ren, “How can smart city shape a happier life? The mechanism for developing a Happiness Driven Smart City,” Sustain. cities Soc., vol. 80, p. 103791, 2022.

[17] A. R. Kunduru, “Machine Learning in Drug Discovery: A Comprehensive Analysis of Applications, Challenges, and Future Directions,” Int. J. Orange Technol., vol. 5, no. 8, pp. 29–37, 2023.

[18] A. Padhi, A. Agarwal, S. K. Saxena, and C. D. S. Katoch, “Transforming clinical virology with AI, machine learning and deep learning: a comprehensive review and outlook,” VirusDisease, vol. 34, no. 3, pp. 345–355, 2023.

[19] M. Pichler and F. Hartig, “Machine learning and deep learning—A review for ecologists,” Methods Ecol. Evol., vol. 14, no. 4, pp. 994–1016, 2023.

[20] V. Tiwari, R. C. Joshi, and M. K. Dutta, “Dense convolutional neural networks based multiclass plant disease detection and classification using leaf images,” Ecol. Inform., vol. 63, p. 101289, 2021.

[21] A. Sherstinsky, “Fundamentals of recurrent neural network (RNN) and long short-term memory (LSTM) network,” Phys. D Nonlinear Phenom., vol. 404, p. 132306, 2020.

[22] A. Khan, A. Sohail, U. Zahoora, and A. S. Qureshi, “A survey of the recent architectures of deep convolutional neural networks,” Artif. Intell. Rev., vol. 53, pp. 5455–5516, 2020.

[23] S. Saponara, A. Elhanashi, and Q. Zheng, “Recreating fingerprint images by convolutional neural network autoencoder architecture,” IEEE Access, vol. 9, pp. 147888–147899, 2021.

[24] C. Zhong, H. Guo, I. Swan, P. Gao, Q. Yao, and H. Li, “Evaluating trends, profits, and risks of global cities in recent urban expansion for advancing sustainable development,” Habitat Int., vol. 138, p. 102869, 2023.

[25] Y. Murayama and R. C. Estoque, “Urbanization: Concept, Mechanism, and Global Implications,” Hum. Geosci., pp. 261–282, 2020.

[26] G. F. Randolph and C. Deuskar, “Urbanization beyond the metropolis: Planning for a large number of small places in the global south,” J. Plan. Educ. Res., p. 0739456X20971705, 2020.

[27] S. Altaf, R. Asad, S. Ahmad, I. Ahmed, M. Abdollahian, and M. Zaindin, “A Hybrid Framework of Deep Learning Techniques to Predict Online Performance of Learners during COVID-19 Pandemic,” Sustainability, vol. 15, no. 15, p. 11731, 2023.

[28] F. Li et al., “Towards big data driven construction industry,” J. Ind. Inf. Integr., p. 100483, 2023.

[29] S. Zepf, J. Hernandez, A. Schmitt, W. Minker, and R. W. Picard, “Driver emotion recognition for intelligent vehicles: A survey,” ACM Comput. Surv., vol. 53, no. 3, pp. 1–30, 2020.

[30] H. Boughanem, H. Ghazouani, and W. Barhoumi, “Facial Emotion Recognition in-the-Wild Using Deep Neural Networks: A Comprehensive Review,” SN Comput. Sci., vol. 5, no. 1, pp. 1–28, 2024.

[31] Y. X. Zheng, K.-W. A. Chee, A. Paul, J. Kim, and H. Lv, “Electronics Engineering Perspectives on Computer Vision Applications: An Overview of Techniques, Sub-areas, Advancements and Future Challenges,” Cut. Edge Appl. Comput. Intell. Tools Tech., pp. 113–142, 2023.

[32] S. Rokhsaritalemi, A. Sadeghi-Niaraki, and S.-M. Choi, “Exploring Emotion Analysis using Artificial Intelligence, Geospatial Information Systems, and Extended Reality for Urban Services,” IEEE Access, 2023.
[33] P. Iamtrakul, S. Chayphong, P. Kantavat, Y. Hayashi, B. Kijsirikul, and Y. Iwahori, “Exploring the Spatial Effects of Built Environment on Quality of Life Related Transportation by Integrating GIS and Deep Learning Approaches,” Sustainability, vol. 15, no. 3, p. 2785, 2023.
[34] L. Zhang and C. Kim, “Chromatics in urban landscapes: Integrating interactive genetic algorithms for sustainable color design in marine cities,” Appl. Sci., vol. 13, no. 18, p. 10306, 2023.
[35] E. AI, “City Happiness Index 2024.” 2024.

BIBLIOGRAPHY OF AUTHORS

Gregorius Airlangga, Received the B.S. degree in information system from the Yos Sudarso Higher School of Computer Science, Purwokerto, Indonesia, in 2014, and the M.Eng. degree in informatics from Atma Jaya Yogyakarta University, Yogyakarta, Indonesia, in 2016. He got Ph.D. degree with the Department of Electrical Engineering, National Chung Cheng University, Taiwan. He is also an Assistant Professor with the Department of Information System, Atma Jaya Catholic University of Indonesia, Jakarta, Indonesia. His research interests include artificial intelligence and software engineering include path planning, machine learning, natural language processing, deep learning, software requirements, software design pattern and software architecture.