The Effectiveness of Identifying Residential Housing using Image Recognition by Artificial Intelligence

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ABSTRACT

Residential housing identification based on satellite imagery has become an important approach in supporting urban planning, disaster management, and regional mapping. This study evaluates the effectiveness of settlement recognition techniques using high-resolution imagery and artificial intelligence (AI) models, specifically deep learning methods based on convolutional neural networks (CNN) and object recognition. The main factors that affect identification accuracy include image spatial resolution, command quality, training data diversity, and the geographic complexity of the observed area. Based on the analysis results, the use of high-resolution imagery combined with image recognition by AI such as Google Gemini can generate an accuracy of 68.4% in calculating the number of buildings. This value tends to be low to achieve a high level of accuracy in calculating the number of buildings therefore it is not recommended to calculate the number of buildings accurately, but it can be used to determine housing availability in a range of values. However, to analyze building density, It can successfully generate complex images of building density according to the conditions of the given image. This process can be used to aid urban planning while emphasizing the importance of selecting data sources, careful selection of commands, and adaptive machine learning models to improve the effectiveness of settlement recognition, especially in areas with complex spatial structures in the fields of regional and urban planning and disaster management.

Keywords : housing pattern, image recognition, wetland, urban development

ABSTRAK

Identifikasi permukiman berbasis citra satelit telah menjadi pendekatan penting dalam mendukung perencanaan kota, manajemen bencana, dan pemetaan wilayah. Studi ini mengevaluasi efektivitas teknik pengenalan permukiman dengan memanfaatkan citra resolusi tinggi dan model kecerdasan buatan (AI), khususnya metode deep learning berbasis convolutional neural networks (CNN) dan rekognisi obyek. Faktor-faktor utama yang mempengaruhi akurasi identifikasi meliputi resolusi spasial citra, kualitas preprocessing, keberagaman data latih, serta kompleksitas geografis kawasan yang diamati. Berdasarkan hasil analisis, penggunaan citra resolusi tinggi dikombinasikan dengan rekognisi gambar oleh AI seperti Google Gemini dan ChatGPT mampu menghasilkan akurasi dalam menghitung jumlah bangunan sebesar 68,4%. Nilai ini cenderung rendah untuk mencapai tingkat akurasi yang tinggi dalam menghitung jumlah bangunan sehingga tidak disarankan untuk menghitung jumlah bangunan secara akurat, namun bisa digunakan untuk menentukan ketersediaan perumahan dalam nilai rentang. Namun untuk menganalisis kepadatan bangunan, AI dapat menghasilkan gambar yang kompleks sesuai dengan kondisi gambar yang diberikan. Dalam proses ini, diperlukan pemilihan sumber data yang baik dan pemilihan command yang tepat untuk meningkatkan efektivitas pengenalan suatu bangunan, terutama di area dengan struktur spasial yang kompleks dalam konteks bidang perencanaan wilayah dan kota serta migitasi bencana..

Kata Kunci : pola perumahan, pengenalan gambar, lahan basah, pembangunan perkotaan

1. INTRODUCTION

The rapid advancement of artificial intelligence processing and image recognition has become one of the research tools for addressing challenges such as less time consuming and somewhat accurate for quick analytical of current situation. Drone, on the other hand, can meet today's standard in capturing image data which is the main advantage as the captured images are the latest situation when compared to satellite images are only considered up to date in major cities. Most satellites images which can freely acquired such as Landsat Satellites by USGS are not in high resolution by pixels and some areas are covered by clouds can be problematic to see individual buildings. These technical problems can be solved by acquiring the image by using drones. The disadvantage of using drones is the process is limited by flight time and the difficulty of surrounding areas.

The increasing population in Indonesia which directly proportional to the need for a place to live is still a challenge for the government to fulfill the lack of proper housing while maintain the minimum impact on the environment. Providing proper housing will contribute to land-use changes in the area especially from open fields, rice paddies, forestry or plantation (Shalihat & Ardiwinata, 2023). Statistic data of housing counts provided by National Data Statistic are updated once of every several years and never stated in exact numbers rather stated in percentage form.

Palembang being one of the fast-growing cities in Indonesia faces the problem such as the need of housing. In an article by Aribowo et. al. (2024), Palembang is the seventh city in Indonesia with a backlog figure reaching 122,932 houses in 2018 as stated by Public Housing Department. The government pushed the agenda of providing low-cost housing as priority to fulfill the need of housing in Palembang). Providing proper housing in the hope of reaching the same opportunity for the any level of community (Darmawan, 2021).

Being one of the densest city populations in Indonesia, Palembang has shown a great development in residential housing in comparison to other neighboring cities such as Prabumulih. Yet when compared to Perth, Australia the housing pattern is distinctively different therefore we can compare how the AI analyze the pattern and the number of houses respectively. In return, AI can be used to monitor and evaluate the best location and the number of houses being built.

Using quantitative approach, we can analyze housing development using spatial patterns and using the aid of artificial intelligence. This analysis consists of data comparison either by traditional method or AI image recognition. In addition, by using two satellite data from 2018 to 2024 and drone images of several areas of study will be the base data.

2. STATEMENT OF PROBLEMS

2.1. Philosophical Origin of Residential Housing and Pattern of Both Cities

Most cities in Indonesia are water-front cities which means most of their developments originates from riverbanks and coastal areas. In another word, Indonesia is a nation fundamentally shaped by its relationship with water. This maritime character has dictated the very origins and patterns of its urban development. Most Indonesian cities, born from the necessity of trade and resource access, are waterfront cities, their growth intrinsically linked to riverbanks and coastal areas. As stated by Fitri, M et. Al (2016) an evident in Palembang, a city that not only straddles the mighty Musi River but is also defined by the expansive wetlands that surround it. The city's evolution is a testament to the profound influence of land typology on urban development.

Palembang, in particular, stands as a prime example of a city whose development is inextricably linked to its watery environment. The Musi River, its lifeblood, has served as the city's primary artery for centuries, facilitating trade, transportation, and cultural exchange. The city's historical significance as the capital of the Srivijaya Empire, a powerful maritime trading kingdom, underscores the crucial role of its riverine location. However, Palembang's unique topography extends beyond the river itself. The surrounding terrain is characterized by extensive wetlands, including peatlands and swamps, which have profoundly influenced the city's urban planning and development.

This wetland environment presents both opportunities and challenges. Historically, Palembang's residents developed ingenious methods to adapt to these conditions, constructing stilt houses and intricate canal systems to navigate the fluctuating water levels. These traditional adaptations demonstrate the city's long-standing ability to coexist with its unique environment. However, rapid urbanization and development have placed increasing pressure on Palembang's fragile wetland ecosystem. Land reclamation, deforestation, and pollution have exacerbated the city's vulnerability to flooding and other environmental hazards (Fitri, M. et al., 2016).

When examining the relationship between urban development and geography, Perth, Western Australia, provides a compelling case study. While not defined by intricate riverine networks like Palembang, Perth's evolution is undeniably shaped by its location along the Swan River and its proximity to the Indian Ocean. This coastal setting, combined with the unique characteristics of the Swan Coastal Plain, has significantly influenced the city's growth and development.

Unlike the wetland topography of Palembang, Perth is situated on the Swan Coastal Plain, a relatively flat expanse of sandy soils. This terrain has allowed for the city's outward expansion, resulting in a sprawling metropolitan area. However, the sandy soils also present challenges, particularly in relation to infrastructure development and water management (Semeniuk, 2013).

However, this coastal location also makes Perth vulnerable to the impacts of climate change, including rising sea levels and coastal erosion. These challenges necessitate careful planning and sustainable development practices to protect the city's coastline and infrastructure.

Furthermore, Perth's geographical isolation has played a significant role in its development. Being one of the most remote major cities in the world, Perth has had to develop a degree of self-reliance and resilience. This isolation has also fostered a unique sense of community and a strong connection to the natural environment.

2.2. Image Recognition in Residential Housing Recognition

The rise of artificial intelligence (AI) is ushering in a new era for urban planning and housing development, particularly through the application of image recognition. This technology, capable of deciphering complex visual data, is proving invaluable in analyzing housing patterns, predicting development trends, and optimizing the design of future residential spaces. In cities like Palembang, where unique geographical and cultural factors influence housing development, AI image recognition offers a powerful tool for understanding and shaping urban landscapes.

At its core, AI image recognition utilizes deep learning algorithms to analyze images, identifying patterns and extracting meaningful information. In the context of housing, this technology can be used to analyze aerial photographs, satellite imagery, and street-level views, providing a comprehensive understanding of existing housing patterns. For instance, AI can identify the density of housing, the types of architectural styles prevalent in a given area, and the distribution of green spaces (Song et al, 2023).

In Palembang's unique wetland environment, AI can play a crucial role in understanding the impact of water management strategies on housing development. By analyzing aerial images over time, AI can track changes in water levels, identify areas prone to flooding, and assess the effectiveness of drainage systems. This information can be used to inform urban planning decisions, ensuring that new housing developments are designed to mitigate the risks associated with the city's wetland topography.

Furthermore, AI image recognition can be used to analyze the evolution of housing patterns over time, revealing trends in urban sprawl and the development of informal settlements. By comparing historical images with current data, AI can identify areas where housing density has increased, where new construction has occurred, and where informal settlements have emerged. This analysis can help urban planners understand the factors driving housing development and develop strategies to address challenges such as overcrowding and inadequate infrastructure (Herold et al., 2003).

In an article written by Ersina (2023) and Santosa & Prihandono (2025) stated that in the design phase of new housing developments, AI image recognition can be used to analyze existing architectural styles and building materials, ensuring that new construction is consistent with the local context. This is particularly important in cities like Palembang, where traditional architectural styles reflect the city's rich cultural heritage. AI can also be used to generate realistic 3D models of proposed housing developments, allowing stakeholders to visualize the final product and make informed decisions.

Beyond urban planning and design, AI image recognition can also be used to assess the condition of existing housing stock. By analyzing images of buildings, AI can identify signs of deterioration, such as cracks, leaks, and structural damage. This information can be used to prioritize maintenance and repairs, ensuring that housing stock remains safe and habitable. In areas with high risk of natural disasters, AI can analyze images of buildings after an event, quickly assessing damage, and prioritizing help.

The application of AI image recognition in housing development also extends to the analysis of social and economic factors. By analyzing images of neighborhoods, AI can identify areas with high concentrations of poverty, inadequate infrastructure, and limited access to essential services. This information can be used to target resources and interventions, ensuring that housing development is equitable and inclusive (Sugandhi et al., 2023).

However, the use of AI image recognition in housing development raises important ethical considerations. The collection and analysis of visual data can raise concerns about privacy, particularly in relation to facial recognition technology and the monitoring of public spaces (Zakiansyah & Sutabri, 2025). It is crucial to establish clear ethical guidelines and regulations to ensure that these technologies are used responsibly and transparently. The accuracy of AI image recognition depends heavily on the quality and quantity of data used to train the algorithms. In the context of housing development, in a journal by Herold et al (2003), this means that it is essential to collect and curate diverse datasets that accurately reflect the range of housing patterns and conditions in a given area.

The integration of AI image recognition into housing development is still in its early stages, but its potential is undeniable. As AI technology continues to advance, we can expect to see even more innovative applications that transform the way we plan, design, and manage our cities. In places like Palembang, AI can be a powerful tool for ensuring that housing development is sustainable, equitable, and responsive to the unique challenges of the city's environment (Song et al., 2023).

2.3. Hypothesis

By combining all types of data and literature reviews on complexity of residential buildings components and artificial intelligence (AI) image recognition, there is a possibility that by a certain method by utilizing computation by AI can successfully analyze and recognize building density of the given area.

3. DATA AND METHODS

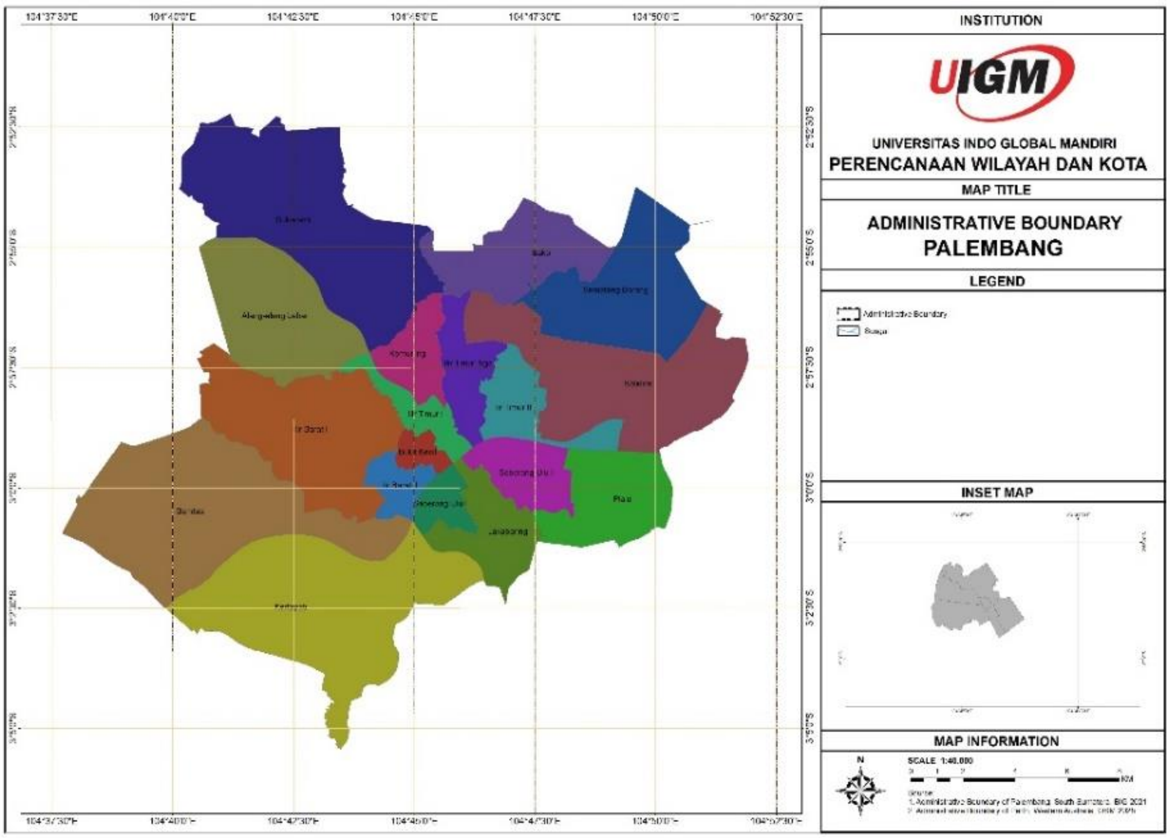
3.1. Data

The types of data used in this research consists of two types, primary and secondary data. Primary data consists of several images derived from aerial drone images of housing patterns in Palembang, Indonesia. Secondary data consists of several images obtained from Google Satellite images of housing patterns in Perth, Australia as both of images can be seen on Picture 1 below.

Picture 1. Residential Housing Pattern in Palembang (Left) and Perth, Australia (Right)

3.2. Area of Study

The research focuses on 2 different cities which are Palembang, Indonesia and Perth, Australia with administrative boundaries of both cities is shown on Picture 2 and Picture 3 below. Both show distinctive differences in housing patterns, size and roof models. Palembang, being the most crowded and mostly scattered of the two and Perth's residential is more towards grid-like pattern. The supporting statement of the choice of the area of study is mainly based on data availability and the complexity of housing patterns especially in Palembang whilst the composition of housing patterns in Perth is in "grid-like" patterns. Both cities are quite similar by having a river that divides the city into 2 areas.

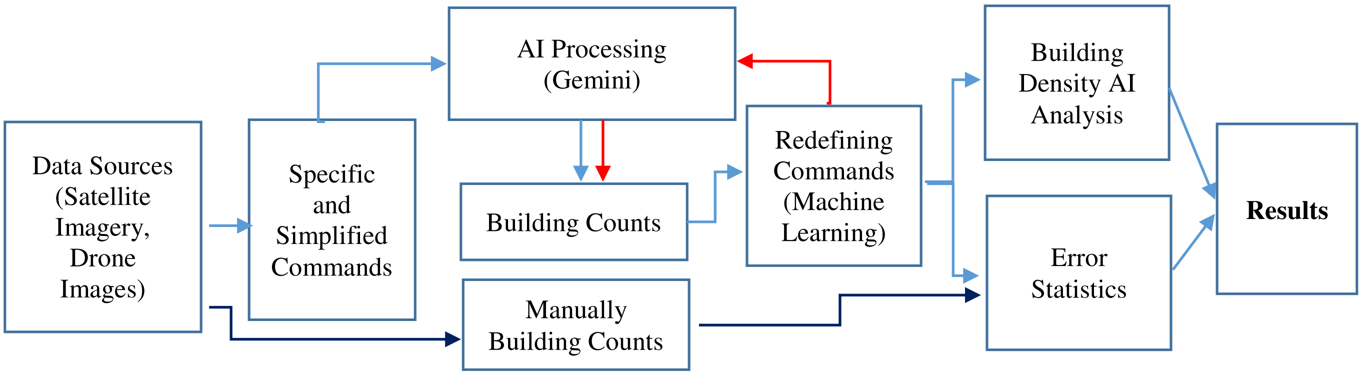


Picture 2. Administrative boundary of Palembang (*BIG, 2021*)

3.3. Research Methods

Building classification using image recognition involves analyzing images typically from satellite, drone, or street-level sources to automatically identify and categorize buildings based on certain attributes. This is widely used in urban planning, GIS (Geographic Information Systems), insurance, and real estate (Song et al., 2023). Image recognition in housing recognition typically refers to the use of computer vision and artificial intelligence techniques to analyze images of houses or housing environments for specific purposes (Herolds et al., 2003).

By using quantitative methods, this paper used two types of analysis. First, we will analyze the housing characteristics derived from Google's Gemini. Then we will identify the number of houses of the given image to Google's Gemini which then can be translated into how AI sees the image and how accurate the results. Here is the workflow of the given analysis:

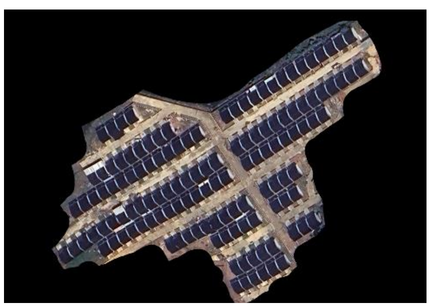


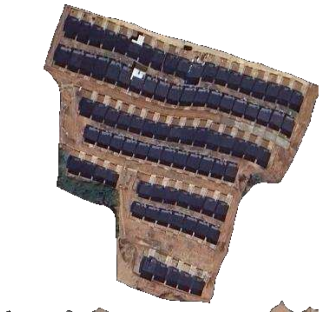
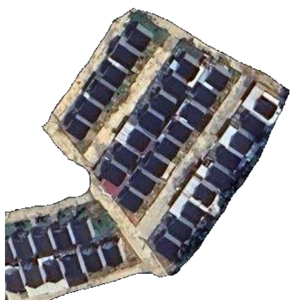
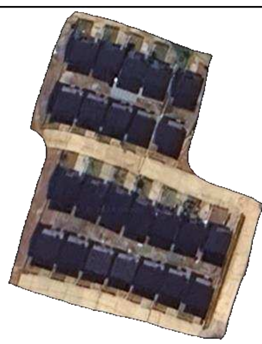
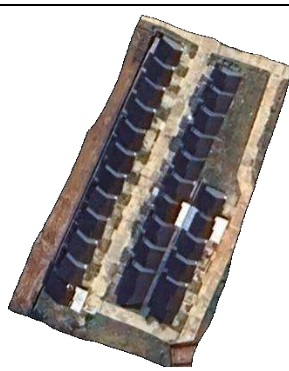
Graphic 1. Workflow of Analysis

4. RESULTS AND DISCUSSIONS

1. Housing characteristics detection

Google's Gemini will be given a series of images consisting of housing patterns of both cities. The houses will be counted by Google's Gemini and compared to what human eyes can see in the images. These sample images were only uploaded once for all analysis to provide consistency of the term Machine Learning. The sample images of the study are shown below:

 **Picture 3.** Sample Image 1	This is ***Sample Image 1*** which located in Palembang, South Sumatera. This is an example of a new residential housing complex with uniform roofing and sizes.
 **Picture 4.** Sample Image 2	This is ***Sample Image 2*** which located in Palembang, South Sumatera. This is an example of an aged residential housing block with different roofing and sizes.

 **Picture 5.** Sample Image 3	This is ***Sample Image 3*** which located in Palembang, South Sumatera. This is an example of a new residential housing complex with uniform roofing and sizes.
 **Picture 6.** Sample Image 4	This is ***Sample Image 4*** which located in Palembang, South Sumatera. This is an example of a new residential housing complex with uniform roofing and sizes.
 **Picture 7.** Sample Image 5	This is ***Sample Image 5*** which located in Palembang, South Sumatera. This is an example of a new residential housing complex with uniform roofing and sizes.
 **Picture 8.** Sample Image 6	This is ***Sample Image 6*** which located in Palembang, South Sumatera. This is an example of a new residential housing complex with uniform roofing and sizes.

 **Picture 9.** Sample Image 7	This is ***Sample Image 7*** which located in Perth, Western Australia. This is an example of a modern residential housing complex with uniform roofing and sizes.
 **Picture 10.** Sample Image 8	This is ***Sample Image 8*** which located in Perth, Western Australia. This is an example of a modern residential housing block with different roofing and sizes along with various amenities.
 **Picture 11.** Sample Image 9	This is ***Sample Image 9*** which located in Perth, Western Australia. This is an example of a modern residential housing block with different roofing and sizes along with various amenities.

2. Image Recognition of Residential Housing Characteristics
   The image recognition by AI using Google's Gemini were conducted towards each image from Sample Image 1 to Sample Image 9. The housing characteristics which derived from Google's Gemini Algorithms were surprisingly dynamic and close to what human eyes can see. Here are the housing characteristics of each image recognized by AI using Google Gemini are shown on table 1 below:

Table 1. Image Recognition of Residential Housing Characteristics

Sample Number	Roof	Amenities	Vegetation
Sample Image 1	False: Solar Panel	True: None	True: None
Sample Image 2	True: House Roof	True: None	True: Exists
Sample Image 3	False: Solar Panel	True: None	True: None
Sample Image 4	False: Solar Panel	True: None	True: None
Sample Image 5	True: AI Learning	True: None	True: None
Sample Image 6	True: AI Learning	True: None	True: None
Sample Image 7	True: House Roof	True: Exists	True: Exists
Sample Image 8	True: House Roof	True: Exists	True: Exists
Sample Image 9	True: House Roof	True: Exists	True: Exists
Accuracy:	**60%**	**100%**	**100%**

As the results shown above, the AI was unable to recognize house roof as the color of the roofs in the images were identified as solar panels array. But when Sample Image 5 was fed into AI, AI learnt that the color of rectangular shape of the roof of the houses. Whilst recognizing Amenities and Vegetation by AI, if exists around the houses can easily be recognized such as swimming pools, solar panels, and patios.

3. Building Counts Accuracy

Building counts from each image were also conducted to analyze the accuracy of each image recognition. These results then compared to manual counts from each respective sample images. Here are the results of building counts by AI as shown on table 2 below:

Table 2. Building Counts

Sample Number	Google's Gemini	Manual Count	% Accuracy
Sample Image 1	408	130	31,8%
Sample Image 2	28	18	64,2%
Sample Image 3	103	88	85,4%
Sample Image 4	20	41	48,7%
Sample Image 5	24	24	100%
Sample Image 6	24	27	88,8%
Sample Image 7	10	10	100%
Sample Image 8	29	10	34,5%
Sample Image 9	20	32	62,5%
Accuracy:			**68,4%**

The accuracy of residential housing being recognized by AI is by average of 68,4%. The least percentage of recognition accuracy is 31,8% with total building count of 408 by AI and 130 by manual count. While the best recognition accuracy of 100% is the image with 10 buildings and image with 24 buildings.

4. Further Process for Residential Pattern

Residential Pattern Analysis (RPA) is a method to analyze residential patterns which can be translated to how the urban sprawl of a city is being built. The first process is to identify Building Density can be obtained from AI by providing sample of satellite imagery which is shown on Picture 12 below. With this data, we can see how much urban sprawl of a city is built. Most urban sprawl based on the image is focused on the main road and spread tightly outwards.

Picture 12. An Aerial View of Residential Housing (a); Building Density Generated by AI (b)

The image of Building Density generated by AI can be seen on Picture 12 (b) above. This image shows there are potential areas for residential housing in green while red-orange-yellow shows the density of the buildings in the area. The green area in the image shows how much vegetation or open area for water catchment area. In a journal by Yao et al. (2018), stated that urbanization caused green spaces to decrease. Which when we cross-reference these findings and the current zoning policies such as RTRW or RDTR, we can update them according to empirical facts.

Residential Building Pattern refers to how well-organized the layout of buildings, roads, and open spaces is in each area. This is an important aspect of urban planning, particularly for identifying slum areas and analyzing spatial patterns. Picture 12 illustrates the level of regularity in residential buildings in Palembang City. In contrast, image (a) shows a regular settlement characterized by neatly arranged, uniform buildings and straight roads laid out in a grid or radial pattern.

Differences in satellite image patterns like these can guide spatial planning based on the condition of residential environments. For instance, they can help assess the vulnerability of buildings to hazards such as flooding or earthquakes (Muin & Rakuasa, 2023). Image interpretation can support better disaster mitigation strategies and reduce overall risk.

5. CONCLUSIONS

This study discusses image recognition as a crucial component in the development of artificial intelligence systems, particularly for automatic object identification. By using feature extraction and classification methods based on feature vectors, image recognition systems can convert visual data into meaningful information. In contrast, AI can help to determine density of buildings in an area of interest but unable to point out the correct number of buildings individually. With an average of 68,4% accuracy, AI still needs to learn to differentiate each building characteristics to achieve higher accuracy.

The research findings indicate that the accuracy of such systems heavily depends on the feature extraction techniques and classification algorithms employed. Therefore, selecting the appropriate command and data sources is a key factor in improving the performance of image recognition systems. This study contributes to a deeper understanding and practical implementation in the fields of digital image processing and artificial intelligence toward urban planning and disaster mitigation as well as how AI will soon be able to connect all the dots towards sustainable development.

6. BIBLIOGRAPHY

Aribowo, D., Sari, D. P., & Prasetyo, L. B.(2024). Analisis Pola Permukiman Berbasis Citra Satelit Resolusi Tinggi Menggunakan Pendekatan GeoAI. *Jurnal Geografi dan Penginderaan Jauh* 12, no. 1: 45–56.

Bhatta, B. (2010). *Analysis of Urban Growth and Sprawl from Remote Sensing Data*. Springer.

Darmawan, R. (2021). Analisis Perubahan Pola Permukiman Menggunakan Citra Satelit Resolusi Menengah. *Jurnal Perencanaan Wilayah dan Kota* 17, no. 2: 89–100.

Ersina, S. (2023). Menciptakan Kota Cerdas: Memanfaatkan AI (Artificial Intelligence) untuk Pengembangan Ruang Publik Perkotaan yang Cerdas. Prosiding Seminar Nasional. E-ISSN: 3025-1591

Fitri, M., Yuliando, H., dan Winarno, D. S.(2016). Analisis Pola Permukiman Menggunakan Citra Resolusi Tinggi di Kota Palembang. *Jurnal Teknologi Informasi dan Ilmu Komputer* 3, no. 2: 123–130.

Goodchild, M. F. (2018). Geospatial artificial intelligence: New questions and opportunities. *Annals of the American Association of Geographers*, 108(1), 1–16.

Herold, M., Goldstein, N. C., & Clarke, K. C. (2003). The spatiotemporal form of urban growth: Measurement, analysis and modeling. *Remote Sensing of Environment*, 86(3), 286–302.

Muin, A., Rakuasa, H. (2023). Pemanfaatan Geographic Artificial Intelligence (Geo-AI) Untuk Identifikasi Daerah Rawan Banjir Di Kota Ambon. Gudang Jurnal Multidisiplin Ilmu, Vol 1; No 2: 58-63.

Santosa, C. A., Prihandono, D. E. (2025). Artificial Intelligent (AI) dan Interior Desainer Suatu Tantangan, Peluang, dan Adaptasi. Jurnal Ispectrum, Vol 1; No 1.

Shalihat, A. K., Ardiwinata, Y., & Natul, A. S. (2023). Utilization of Spatial Data for Analysis of Land Use Change in Karya Jaya Village, Kertapati District, Palembang City (2018-2022): Pemanfaatan Data Spasial Untuk Analisis Perubahan Penggunaan Lahan Di Kelurahan Karya Jaya Kecamatan Kertapati Kota Palembang (2018-2022). *Jurnal Tekno Global*, *12*(01), 36–40. https://doi.org/10.36982/jtg.v12i01.3158.

Semeniuk, C.A., Semeniuk, V. The response of basin wetlands to climate changes: a review of case studies from the Swan Coastal Plain, south-western Australia. *Hydrobiologia* **708**, 45–67 (2013). https://doi.org/10.1007/s10750-012-1161-6

Song, Y., Kalacska, M., Gasparovic, M., Yao, J., & Najibi, N. (2023). Advances in geocomputation and geospatial artificial intelligence (GeoAI) for mapping. International Journal of Applied Earth Observation and Geoinformation.

Sugandhi, N., Rakuasa, H., Zainudin., Wahab, A. W., Kamiludin, Jaelani, A., Ramdhani, & Rinaldi, M. (2023). Ulil Albab: Jurnal Ilmiah Multidisiplin, 2(5), 1685-1692.

Yao, R., Cao, J., Wong, L., Zhang, W., Wu, X. (2018). Urbanization Effects on vegetation cover in major African cities during 2001-2017. International Journal of Applied Earth Observation and Geoinformation, Vol 75, 44-53.

Zakiansyah, M., Sutabri, T. (2025. Integrasi Internet of Things (IoT) dan Kecerdasan Buatan (AI) untuk Smart City di Indonesia. Kampus Akademik Publishing: Jurnal Sains Student Research, 3(2), https://doi.org/10.61722/jssr.v3i2.4315