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Implementing Support Vector Machine Algorithm for Early Slums Identification in Yogyakarta City, Indonesia Using Pleiades Images

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Abstract
Slums are one of the urban problems that continue to get the attention of the government and the city of Yogyakarta. Over time, cities continue to experience changes in land use due to population growth and migration. Therefore, it is necessary to monitor the existence of slums continuously. The objectives of this study are to conduct early identification of the slum using the Support Vector Machine (SVM) Algorithm. The data used are Pleiades Image, administrative maps, and existing slum maps of the KOTAKU Program, which are used to test the accuracy. We applied SVM to the Pleiades Image in parts of Yogyakarta City to identify the slum areas. The result of the slum mapping generated from the SVM was compared to the Slum Map of the KOTAKU Program to test the accuracy. The parameters used for early identification of the slums are the characteristics of the object (characteristics of buildings), settlement (density and shape), and the environment (location and its proximity to rivers and industries). We separate slum and non-slum based on texture, morphology, and spectral approaches. Based on the accuracy test results between the SVM classification results map of the slum and the map from the KOTAKU Program, the accuracy is 86.25% with a kappa coefficient of 0.796.

Keywords: Slum, Machine Learning, Support Vector Machine.

1. Introduction

Slums provide significant difficulty in numerous prominent urban areas (Ikuteyijo *et al.*, 2022; Liu & Zhang, 2020; Shekhar, 2020). Slums are settlement areas that have decreased the quality of their function as living places (Celhay & Gil, 2020). These informal settlements arise due to accelerated urbanization, inadequate housing provisions, and constrained economic prospects (Parikh *et al.*, 2020). Slum areas frequently experience a deficiency in fundamental utilities such as access to clean water, adequate sanitation facilities, and healthcare services, intensifying poverty and health inequalities (Sinharoy *et al.*, 2019). The perpetuation of social inequality is facilitated by a recurring pattern involving overcrowding, insufficient infrastructure, and restricted educational opportunities. Governments endeavor to tackle this matter by implementing housing and development initiatives to uplift residents of slums.

The City of Yogyakarta is one of the major cities in Indonesia that experiences the problem of slums. Based on data from the KOTAKU, which stands for Kota Tanpa Kumuh (City Without Slum) Program, Yogyakarta has a slum area of 264.9 hectares. The location of the slum in the city of Yogyakarta is stipulated by the Decree of the Mayor of Yogyakarta, Number 216 of the year 2016. In general, slums in Yogyakarta are located along rivers, such as the banks of the Code River, Winongo River, and Gajah Wong River. The three riverbanks have become a developing slum in the city of Yogyakarta. According to the DIY Provincial Settlement and Infrastructure Service, there are 10 locations of priority slum settlements which are located in Bumijo, Kricak, Tegalrejo, Prawirodirjan, Ngupasan, Sorosutan, Purbayan, Brontokusuman, Baciro, and Klitren villages. Of those 10 locations, the areas to be handled are mainly slums along the river.

The government has made regulations through Article 1 (13) of the Law No. 1 of 2011 on housing and settlement areas, explaining that slums are areas that are not suitable for habitation due to building irregularities, high levels of building density, and quality of buildings, facilities, and infrastructure that do not meet the requirements. Since the issuance of this decree, the government has made efforts every year to organize slums so that currently, there are only 70 hectares of slum areas that have not been reorganized. Therefore, a technology that can help identify housing conditions in urban areas is needed so that the growth of slum areas can be monitored. To support government programs, remote sensing disciplines can help identify slum areas by utilizing remote sensing technology.

Remote sensing has been used for mapping land use/land cover (Shaw & Das, 2018; Ul Din & Mak, 2021). It is also important in mapping slum areas, and its application has been observed across a wide range of data sources and approaches (Kuffer, 2016; Wurm *et al.*, 2017; Tesfay, 2018; Wang *et al.*, 2019; MacTavish *et al.*, 2023; Jitt-Aer & Miyazaki, 2023). Nevertheless, the exploration of the potential application of Pleiades images, in combination with Support Vector Machines (SVM) as the algorithm for the classification, has not been extensively studied (Li *et al.*, 2023). Using Support Vector Machines (SVM) for high-resolution Pleiades data classification can improve the accuracy of slum mapping by effectively classifying and distinguishing intricate slum characteristics. Hence, an untapped potential exists to utilize the combined capabilities of Pleiades imagery and Support Vector Machines (SVM) to enhance the accuracy and efficiency of slum area mapping. This innovative methodology has the potential for enhancing urban planning, allocating resources more effectively, and implementing focused interventions in developing and managing slums.

This study aims to achieve early identification of slums using the Support Vector Machine (SVM) Algorithm. The SVM Algorithm will be applied to Pleiades satellite images within specific areas of the City of Yogyakarta. Subsequently, the accuracy of the generated slum mapping results from the SVM model will be tested against the Slum Map of the KOTAKU Program, contributing to the advancement of accurate slum identification and mapping techniques.

2. Research Methods

2.1. Study Area

This research was located in a part of Yogyakarta City where slums were not handled (Figure 1). Yogyakarta City, positioned as the Special Region of Yogyakarta (DIY) capital in Indonesia, boasts a significant socio-economic significance. Positioned centrally within the region, Sleman Regency borders it to the north, Bantul Regency and Sleman Regency to the east, Bantul Regency to the south, and Bantul Regency and Sleman Regency to the west. The city's administrative expanse spans 32.5km², constituting around 1.025% of DIY's total area. Its landscape is relatively even from west to east, featuring a slight north-south gradient of approximately 1 degree. Yogyakarta City encompasses 14 districts, where Umbulharjo stands as the largest in both land area (8.12km²) and population (90,775), juxtaposed with Pakualaman as the smallest district in terms of both land area (0.63km²) and population (9,341). The city is uniquely marked by the presence of three rivers coursing through its terrain, intricately interwoven with residential settlements: the Gajah Wong River to the east, Code River in the central area, and the Winongo River to the west (Yogyakarta, 2020).

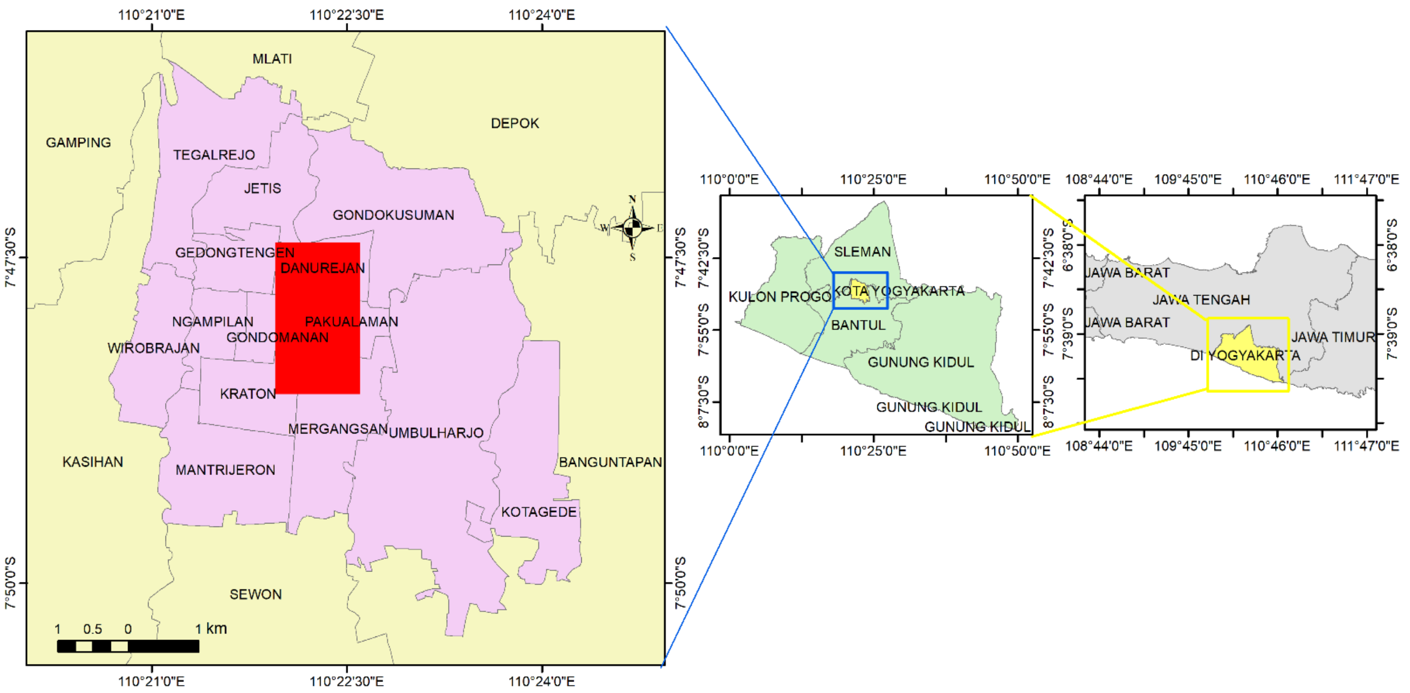

Figure 1. Study Area.

Despite its strategic significance, Yogyakarta grapples with challenges linked to widespread slum areas, a concern mirrored in various nations. These pockets of underprivileged living conditions often cluster along the banks of major rivers, including Kali Winongo, Kali Code, and Kali Gajah Wong, demarcating the region into distinct sections. These settlements have evolved due to poverty, limited job opportunities, and inadequate habitation conditions. The Yogyakarta government has rolled out diverse policies and initiatives to counter this issue. One such endeavor, the Kampong Improvement Program, seeks to uplift living standards via infrastructural enhancements, sanitation improvements, drainage systems, clean water provisions, and integrated waste management. Despite these efforts, the challenge of providing appropriate housing persists. A range of policies has been implemented to mitigate potential issues, encompassing initiatives like Social Rehabilitation of Slum Areas (RSDK), Social Welfare Business Development (PUKSM), Skill Enhancement Projects (PPKT), Clean River Projects (Prokasih), and Urban Settlement Environmental Health Projects (PLKP), among others (Kamim, 2019).

2.2. Research Framework

Figure 2 illustrates the comprehensive workflow employed throughout the course of this study. The research was facilitated by a suite of tools and resources, including computer systems equipped with ArcGIS, ENVI, and RStudio software for adept image processing and cartographic rendering. Additionally, GPS technology was harnessed to ascertain field coordinates precisely. Meanwhile, utilizing the Pleiades 1B Satellite Image captured in 2018, showcasing Yogyakarta City provided pivotal insights into identifying key slum parameters. For precision assessment, the Slum Location Map sourced from the KOTAKU Program was employed.

Establishing a comprehensive spectral depiction of slum features rested upon a twofold foundation: diligent field observations and exhaustive exploration of relevant literature to comprehend the intricacies of slum characteristics within Yogyakarta City. Drawing on the insights of Lonita (2018), the study extracted various indicators crucial to effective slum mapping through remote sensing data. These indicators encompass multifaceted aspects such as geographical placement, settlement patterns, density metrics, accessibility via road networks, distinguishing structural attributes of dwellings, and the extent of vegetative cover in the region. Subsequently, the Pleiades satellite image underwent meticulous processing stages. Radiometric correction was initially conducted to enhance the accuracy of the image data. Concurrently, the collection of slum criteria data ensued, employing the delineated criteria enumerated in Table 1. These criteria functioned as guiding parameters for effectively identifying and characterizing slum settlements within the image.

The culmination of this phase led to the normalization and classification procedures, which were undertaken in accordance with the systematic steps presented in Figure 2. These steps encapsulated intricate processes to transform raw data into meaningful insights, facilitating the categorization and differentiation of slum features based on predefined criteria.

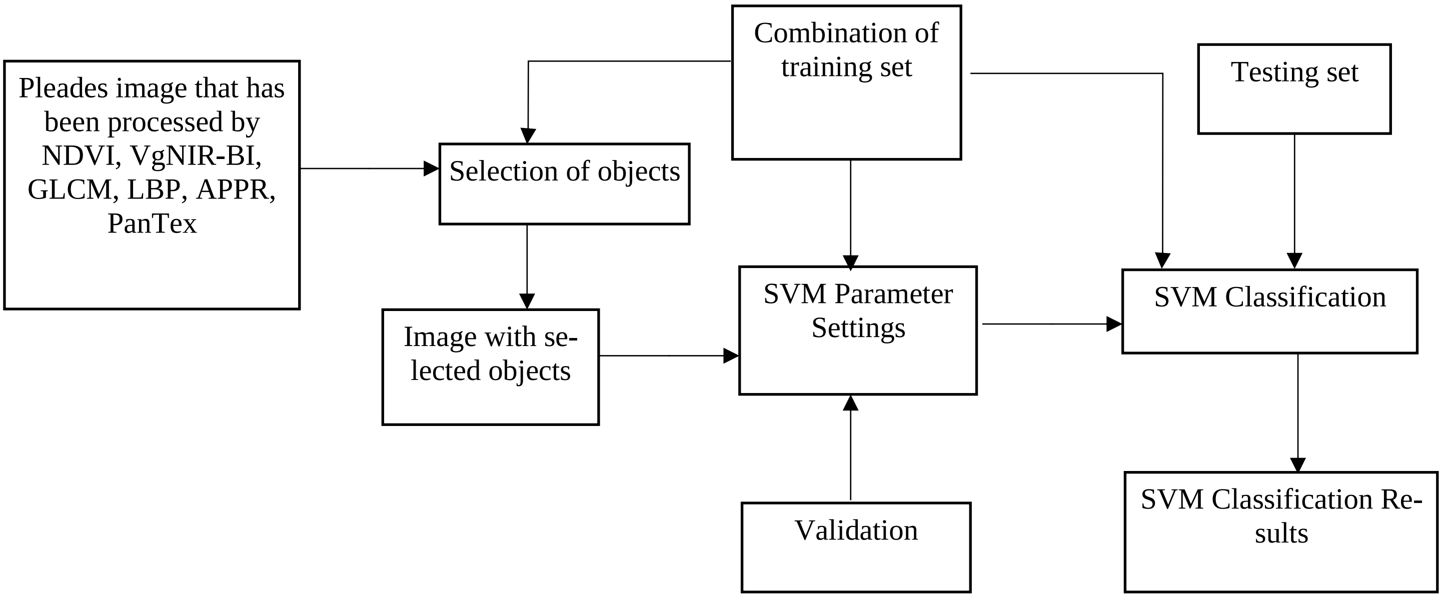

Figure 2. Research Flow Diagram.

Leveraging the Pleiades satellite imagery, an advanced Support Vector Machine (SVM) technique has been methodically developed to identify and delineate slum areas within intricate urban landscapes (Figure 2). The methodology kicks off with an exhaustive preprocessing of the Pleiades image. In this phase, the Normalized Difference Vegetation Index (NDVI) is applied as a pivotal metric to gauge the health of vegetation, singling out zones of active photosynthesis. Complementing this, the Visible Green-Near Infrared Band Index (VgNIR-BI), operating within specific bands of the visible green and near-infrared spectrum, offers further granularity to vegetation and other specific feature data. The Gray Level Co-occurrence Matrix (GLCM) and the Local Binary Pattern (LBP) are incorporated to unearth the spatial nuances and textures inherent in the urban tapestry. The GLCM fetches intricate patterns by assessing the relationships between pixel values, while the LBP provides a binary representation of local textures based on neighboring pixel juxtapositions. The role of Another Pattern Recognition (APPR), albeit not clarified in detail, is likely geared toward enhancing texture or structural interpretation. Meanwhile, the Panoramic Texture (PanTex) index, specifically crafted to discern urban imprints, facilitates the distinction between human-made constructions and untouched natural expanses. This multifaceted preprocessing ambit turns the initial image into a data-rich matrix infused with detailed spatial, textural, and spectral insights.

Following this, the data amassed—including results from the Normalized Difference Vegetation Index (NDVI), Visible green-Near Infrared Band Index (VgNIR-BI), Gray Level Co-occurrence Matrix (GLCM), Local Binary Pattern (LBP), Another Pattern Recognition (APPR), and Panoramic Texture (PanTex) methodologies—are harnessed for precise slum demarcation. This phase involves a supervised classification technique, where a predefined training set, already loaded with discernible slum attributes, is utilized. By acquainting the system with these known slum patterns, it can detect analogous footprints in the broader dataset, culminating in a refined image with prominently highlighted slums.

The subsequent layer of this approach focuses on the fine-tuning of Support Vector Machine (SVM) parameters. SVM, renowned for its capability to delineate the best hyperplane segregating a dataset into distinct classes, demands meticulous tuning for peak performance. By amalgamating both the training set and the slum-highlighted image in this calibration process, SVM undergoes nuanced adjustments, pivoting on factors like regularization, kernel choice, and the kernel settings' peculiarities. This ensures that the SVM algorithm resonates with the signature characteristics of slums identified in the training dataset and the intricate spatial patterns observed in the broader Pleiades image.

Finally, the optimized Support Vector Machine (SVM) parameters, harmonized with the training and testing sets, are propelled into the SVM Classification phase. The SVM, leveraging its core strengths of pattern discernment and data categorization, uses the meticulously preprocessed Pleiades image and its optimized settings to segment the urban realm into distinct facets: slums, non-slums, vegetation zones, and water bodies. This granular, delineated output, culminating in rigorous SVM optimization and cohesive dataset interplay, furnishes stakeholders with a profound, panoramic view of the varied urban and natural dynamics across the surveyed territory.

Table 1. Criteria and Processes Applied to Images.

Slum Criteria	Identifier	Image Features	Image Process
Shape/Pattern	Having an irregular pattern,	Texture approach extraction (panTex, LBP, GLCM) and morphological approach (APPR)	GLCM
	Forming an elongated formation following a river or railroad	Texture approach extraction (panTex, LBP, GLCM) and morphological approach (APPR)	GLCM
Density	High density (more than 250 buildings/ha), tight roof cover	Texture approach extraction (panTex, LBP, GLCM), Spectral approach (VgNIR-BI)	$VgNIR-BI = \frac{Green - NIR}{Green + NIR}$
Vegetation	Low vegetation cover NDVI >0.3	Spectral Approach (NDVI)	$NDVI = \frac{NIR - R}{NIR + R}$

In image processing and analysis, the Gray Level Co-occurrence Matrix (GLCM) stands out as a pivotal method for extracting textural features, enabling the precise identification of target zones or regions of interest (ROI) within a given image. This matrix elucidates patterns by assessing the frequency with which specific combinations of pixel brightness values (gray levels) occur in an image, especially concerning spatial relationships. Within this study, special emphasis was laid on two key GLCM parameters: contrast and variance. The contrast parameter effectively represents the magnitude of the image's local variations in gray levels. A higher contrast value can indicate pronounced edges, potential disturbances, or intricate textural details—often visualized as wrinkles or undulations in the image's fabric. On the other hand, variance serves as a metric to gauge the distribution spread of these gray levels, elucidating the dispersion or concentration of certain pixel values relative to the mean. For a comprehensive understanding of the mathematical computations that underlie these parameters, one can refer to Table 3.

Table 3. Contrast and Variance Formulas in GLCM.

Parameter	Function	Formula
Contrast	A high contrast value indicates the presence of edges, disturbances, or texture wrinkles in the image representing the amount of local gray level variation in the image.	$\sum_{i,j=0}^{n-1} P_{i,j}\,(i-j)^2$
Variance	Measuring the spread of the gray-level distribution	$\sum_{i,j=0}^{n-1} \frac{(i-\mu)(j-\mu_{j)}}{\sigma_i \sigma_j}$

3. Results and Discussion

3.1. Slum Areas Identification

Slum identification using Pleiades Image requires image preprocessing stages in the form of geometric correction and radiometric correction. The geometric correction of high-resolution images is carried out using an orthorectification process of satellite images preceded by measurements of GCP (Ground Control Point) and ICP (Independent Control Point) control points in the field. The selection of objects used as GCP and ICP points is determined with the following considerations: can be identified clearly and accurately on the image in that resolution; the object must be at ground level; the object is not a shadow; objects do not have the same pattern; the condition of the object is permanent and stationary; and it is believed that the object will not change or shift when measuring with GNSS (Global Navigation Satellite System).

Radiometric correction aims to eliminate the effects of atmospheric interference on the image. This research was conducted with corrections to the reflectance level (atmospheric correction). Atmospheric correction is needed so that the image quality is good. Atmospheric correction used is the Quick Atmospheric Correction (QUAC) method.

Extraction of parameters to identify slums consists of GLCM (Gray-Level Co-occurrence Matrix), NDVI, and multispectral channels. Each parameter was extracted directly from the corrected Pleiades-1B image. The SVM algorithm performs best in mapping slums (Wielend, 2014). The details of the parameters and the number of layers extracted from the Pleiades image in this study can be seen in Table 4.

Table 4. Parameters, Features, and Number of Layers for SVM.

Parameter	Features	Number of Layers
Multispectral Channels	Blue, green, red, and NIR channels	4
NDVI	NDVI Index	1
GLCM	- GLCM variance and contrast of blue channels - GLCM variance and contrast of green channels - GLCM variance and contrast of red channel - GLCM variance and contrast of NIR channels	8
Number of Layers		13

NDVI processing is used to detect vegetation density. In general, slums have low or no vegetation density. Figure 3 shows the results of the vegetation index processing on the Pleiades image. The lowest vegetation index value is -0.23, and the highest is 0.65. These results show that settlements dominate this area, so the vegetation cover is only a small percentage—the darker the green, the denser, and the higher the vegetation index value.

Identification using morphological, texture, and spectral criteria is the most widely used in machine learning to identify slums. The blue, green, red, and infrared channels are subjected to the GLCM process before classification. This analysis is usually used as an intermediate process to classify and interpret images. The GLCM method is a statistical method where the statistical calculation uses a gray degree distribution (histogram) by measuring the contrast, granularity, and roughness of an area from the neighbor relationship between pixels in the image (Giannini, 2012).

The user defines a movable window and forms a matrix of shared events. The window sizes used in this study are: 5 x 5; 7 x 7; 9 x 9; 15 x 15; and 21 x 21. The GLCM results for each window can be seen in Figure 4. Classification of Pleiades images using Region of Interest for the classification of 4 types, namely: slum (region01), vegetation (region02), body of water (region03), and non-slum built-up land (region04). Based on the accuracy test results, GLCM with windows size 21x21 was obtained, which produced the best accuracy of 86.25%, with a kappa coefficient of 0.796. In detail, the accuracy testing can be seen in Table 5.

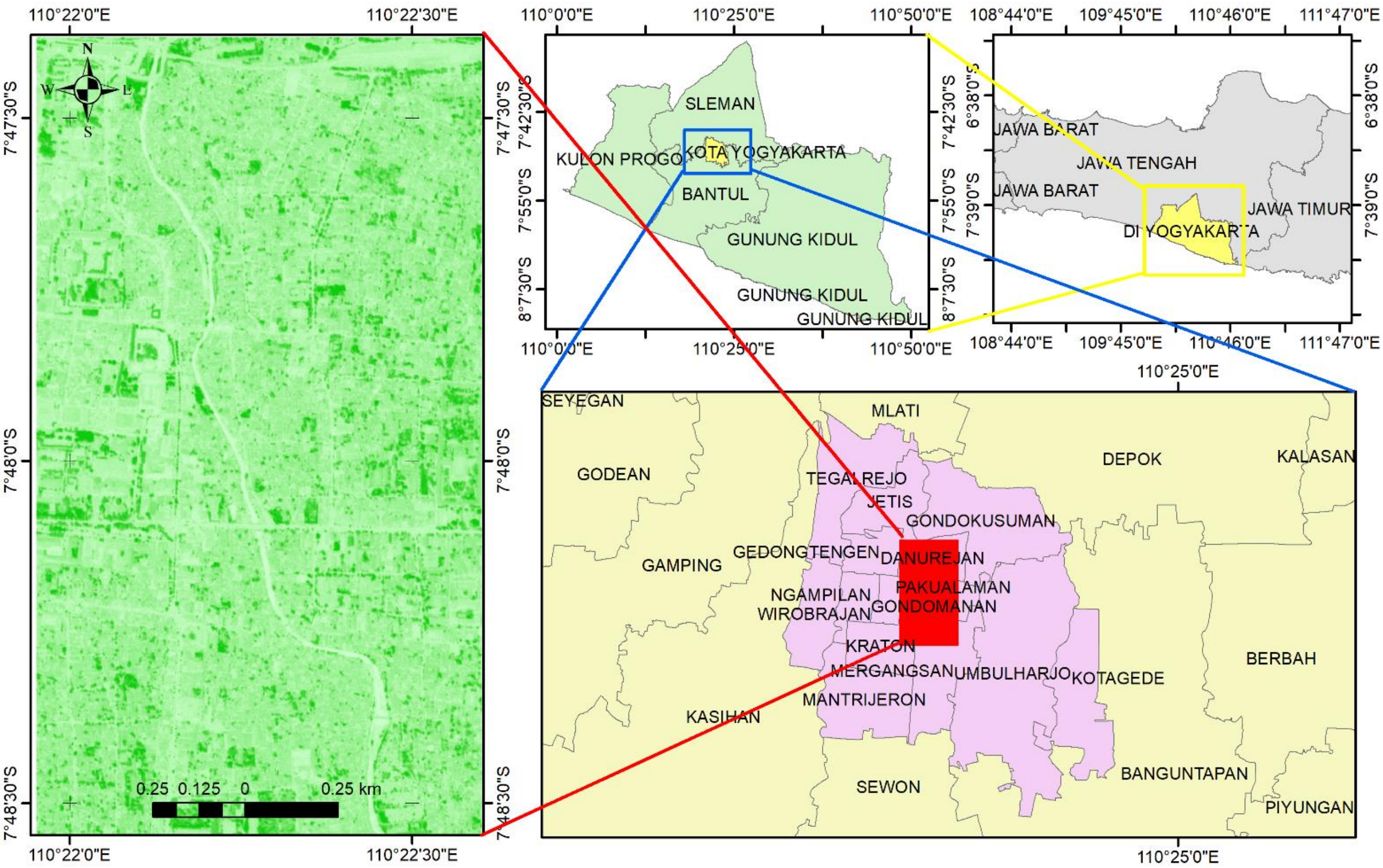

Figure 3. NDVI Processing Results.

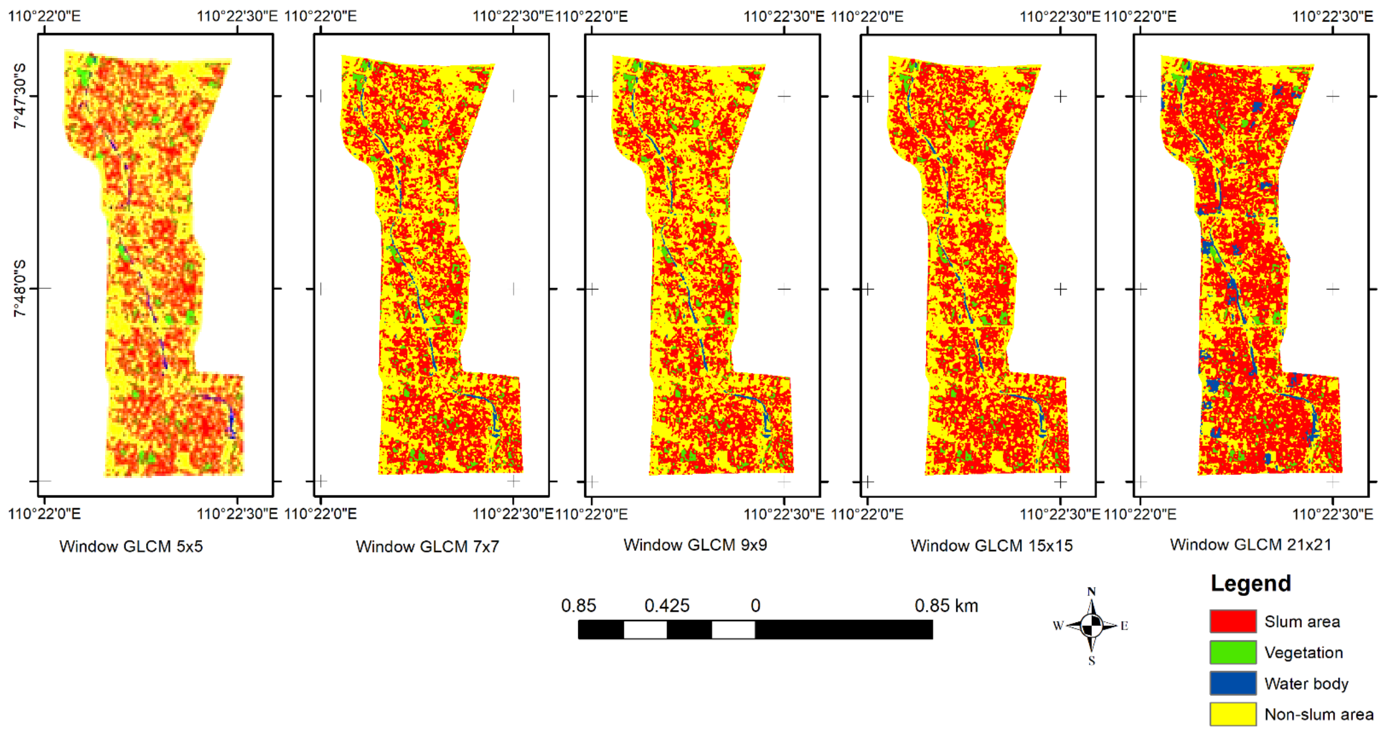

Figure 4. The GLCM Results for Each Window.

Table 5. Slum Identification Accuracy Test.

Classification	**Slums**	**Vegeta-tion**	**Body of water**	**Land built non slum**	**Total**
Slums	429	1	0	48	478
Vegetation	0	147	0	0	147
Body of water	0	0	108	14	122
non-slum built-up land	78	0	29	382	489
Total	507	148	137	444	1236

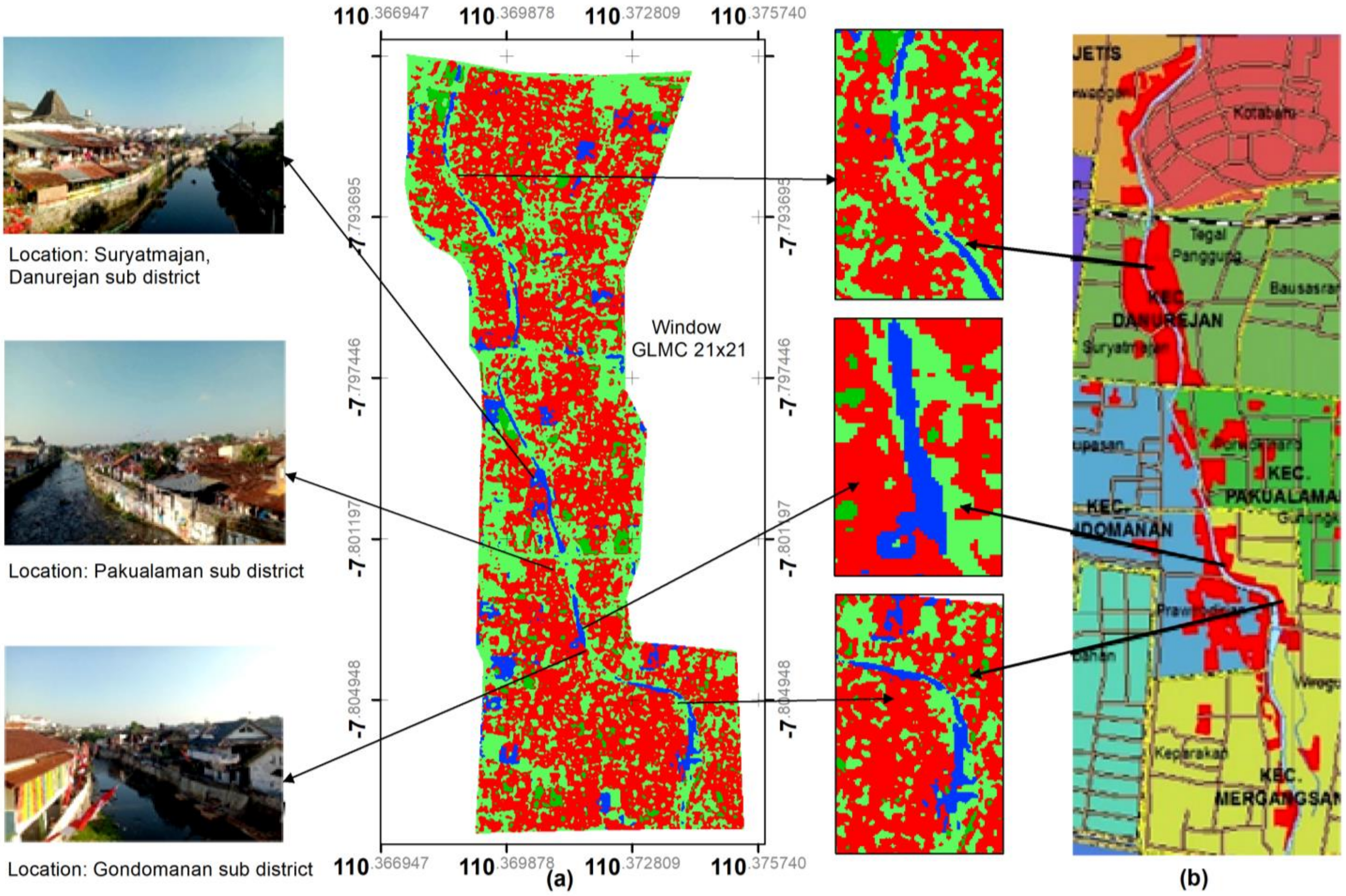

Figure 5. (a) Slum Settlement Identification Results using SVM, (b) Slum Settlement Map Pieces from the KOTAKU Program.

Results testing was also carried out using slum maps from the KOTAKU Program. Based on the overlay between the Slum Map from the KOTAKU Program and the results of the identification of slums using the SVM, it is found that there is compatibility, especially in the riverside area. Along the banks of the Code River, especially in parts of the Jetis District, Danurejan District, Gondomanan District, and Pakualaman District, there are slum settlements from the results of the KOTAKU Mapping program, as well as the identification results with Pleiades imagery using the SVM method.

3.2. Discussion

The present study focuses on a crucial objective, which is the detection and categorization of slum areas, utilizing the capabilities offered by Pleiades satellite photography. This endeavor entails a systematic series of preprocessing phases, each specifically crafted to augment the precision and excellence of the study. The process of geometric rectification, which is considered a fundamental procedure, utilizes the efficacy of ground control and independent control points. The perfect reproduction of real-world topography is achieved through painstaking adjustment of the spatial location of the images, incorporating the following points. The importance of this procedure should not be underestimated, as precise spatial positioning is crucial for effective analysis and subsequent decision-making.

Additionally, the research acknowledges the necessity of addressing the effects of atmospheric interference on the quality of the imagery. To tackle this issue, radiometric correction, specifically atmospheric correction using the Quick Atmospheric Correction (QUAC) approach, is implemented (Bernstein *et al.*, 2012, 2005). This correction technique aims to improve the image's overall quality by mitigating aberrations caused by atmospheric circumstances. The study aims to enhance the accuracy of slum identification by minimizing the impact of external factors, thereby providing a more genuine depiction of the target areas.

Several slum identification methods have been used, including visual interpretation, contour models, OBIA, morphological and texture approaches, pixel-based classification, statistical modeling, and machine learning. The use of remote sensing data to identify slums that rank highest is the use of the OBIA method. Widayani (2018) has identified slums in parts of Yogyakarta City using the OBIA method with special results accuracy on the riverbanks of 82.14%. Leonita (2018) used the Machine Learning method to identify slums in Bandung City with an accuracy of results of 88.5%. Doque (2017) used the SVM algorithm to identify slums in Argentina, Columbia, and Brazil with good results, indicated by F2 Score = >0.81.

The essence of the methodology for identifying slums revolves around extracting pertinent information from the corrected Pleiades image. The derived parameters encompass the Gray-Level Co-occurrence Matrix (GLCM), the Normalized Difference Vegetation Index (NDVI), and data from multispectral channels. These parameters encapsulate critical components of the image, capturing a broad spectrum of characteristics, including textural details (Kiema, 2002; Sandborn and Engstrom, 2016) and the density of vegetation (Engstrom *et al.*, 2019; Saputra *et al.*, 2023). Afterwards, the parameters that have been retrieved are utilized as input for a classification procedure, utilizing the Support Vector Machine (SVM) algorithm. The Support Vector Machine (SVM) is widely recognized for its efficacy in actual implementations and its solid theoretical underpinnings. It operates by adhering to the principle of Structural Risk Minimization (SRM) (Junli and Licheng, 2000). The support vector machine (SVM) algorithm provides a reliable approach for identifying slums by finding the ideal hyperplane that effectively separates different classes within the input space.

The present work presents a comprehensive methodology for identifying slums. Nevertheless, it is important to acknowledge and address certain limitations. A noteworthy constraint is associated with the dependence on terrestrial control points for geometric correction. While control points enhance the precision of spatial alignment, they can also add potential inaccuracies due to shifts or alterations in the surrounding environment over time. Moreover, the research focuses on formal urban settlements, potentially neglecting the intricacies of mixed land-use regions or informal settlements that may deviate from conventional slum categorizations.

Furthermore, it should be noted that the performance of Support Vector Machines (SVM) can be influenced by the quality of the data and the selection of hyperparameters. Therefore, it is essential to conduct a thorough investigation of these factors to understand and optimize the performance of SVM fully. Notwithstanding these constraints, the study establishes a pivotal groundwork for future investigations in the field of slum identification and urban development analysis through high-resolution satellite data.

The effectiveness of the Support Vector Machine (SVM) algorithm in detecting slums is a notable component of this study. The Support Vector Machine (SVM) is a highly adaptable and robust machine learning methodology widely recognized for its practical efficacy and strong theoretical foundations (Dong *et al.*, 2020). The technique is based on Structural Risk Minimization (SRM), which aims to identify the most suitable hyperplane for efficiently distinguishing different classes in the input space (Karaçalı *et al.*, 2004). The approach described in this work has been applied in several geographical locations worldwide, successfully identifying slum areas (Byun, 2003). The utilization of Support Vector Machines (SVM) in this research highlights its ability to manage intricate spatial data and generate well-informed classifications effectively. Our study supports the finding from Kuffer (2016) that machine learning methods such as SVM can enhance the accuracy of slum identification.

The adaptability of Support Vector Machines (SVM) extends beyond the identification of slums, encompassing other domains like image recognition and bioinformatics. The support vector machine (SVM) is proficient at managing datasets with many dimensions (Ghaddar and Naoum-Sawaya, 2018) and adeptly navigate complex decision limits, making it a vital tool in data-driven analytics. The study leverages the integration of Support Vector Machines (SVM) inside the framework for identifying slums, taking advantage of a well-established and robust method. This integration serves to enhance the credibility and reliability of the classification outcomes.

Potential future research in this field may seek to overcome the constraints above by investigating more complex geometric rectification techniques that integrate more sophisticated spatial registration methods. These methods could involve the incorporation of new sensor data or the utilization of machine learning algorithms. The research could explore ensemble methods that integrate many algorithms or utilize deep learning structures to capture intricate patterns within the data more effectively to improve categorization accuracy. In addition, the integration of temporal data and historical photography can facilitate the examination of transformations in slum regions over time and evaluate urban development's intricacies. In conclusion, the examination of the incorporation of supplementary data sources, such as socio-economic indicators or land tenure information, has the potential to yield a more holistic comprehension of slum regions and their attributes.

4. Conclusion

This study offers a meticulous and systematic approach to identifying slum areas through using Pleiades satellite imagery. Integrating geometric and radiometric corrections, along with parameter extraction and SVM-based classification, forms a robust framework for accurate slum identification. However, it is important to acknowledge the study's limitations, including potential inaccuracies arising from control point accuracy, the intricate nature of slum definitions, and the varying performance of the SVM algorithm under different conditions. Despite these constraints, the study lays a foundation for future progress in the field, pointing towards promising directions such as advanced geometric correction methods, ensemble learning strategies, and the incorporation of supplementary data sources. As the synergy between remote sensing and machine learning continues to evolve, this study stands as a pivotal milestone, propelling us towards enhanced precision and deeper insights in urban development analysis. Notably, applying the Support Vector Machine (SVM) algorithm to the Pleiades Image exhibits its potential in detecting slum settlements along rivers, employing NDVI and GLCM parameters. The study's accurate classification results, as validated through comparison with the KOTAKU Program map, demonstrate an impressive accuracy rate of 86.25% and a kappa coefficient of 0.796, affirming SVM's effectiveness in contributing to informed urban planning and development decisions.

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Author Contributions

Conceptualization: Prima Widayani, Achmad Fadilah, Irfan Zaki Irawan; **methodology**: Prima Widayani, Achmad Fadilah, Irfan Zaki Irawan; **investigation**: Prima Widayani, Achmad Fadilah, Irfan Zaki Irawan; **writing—original draft preparation**: Prima Widayani, Achmad Fadilah, Irfan Zaki Irawan; **writing—review and editing**: Prima Widayani, Achmad Fadilah, Irfan Zaki Irawan, Kapil Ghosh; **visualization**: Prima Widayani, Achmad Fadilah, Irfan Zaki Irawan, Kapil Ghosh. All authors have read and agreed to the published version of the manuscript.

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