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Using K-Means Clustering to Analyze Socio-Economic Welfare of Oil Palm Farmers for Decision Support and Contextual Learning Integration

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Abstract: This study aims to cluster the welfare levels of oil palm farmers in Gading Sari Village, Tapung, using the K-Means Clustering algorithm. The analyzed variables include land area, family dependents, average monthly income, additional income, and educational attainment. Previous studies have extensively discussed the welfare of oil palm farmers. This research uses clustering methods to uncover new and more detailed findings about the welfare of oil palm farmers in rural areas. This approach offers a fresh perspective and can be utilized to support data-driven decision-making processes by the government. Data were collected through interviews with 111 oil palm farmers, processed through normalization, and analyzed using the elbow method to identify the optimal number of clusters. The results identified three main clusters: low, medium, and high welfare levels. Land area and average monthly income were the most significant differentiating factors among the clusters. This study's fundamental distinction lies in applying the K-Means algorithm to integrate the socioeconomic aspects of oil palm farmers into specific clusters. These clusters will provide new insights into their welfare conditions. The findings are expected to assist governments and stakeholders in designing more effective and targeted development programs for oil palm

Keywords: Gading Sari Village; K-Means clustering; Oil palm farmer welfare; Socioeconomic analysis

Introduction

Oil palm is one of the key sectors supporting Indonesia's economic growth in agriculture (Purnomo et al., 2020). It has significantly contributed to export revenues and provides a vital means of livelihood for millions of rural households throughout the country (Krishna & Kubitza, 2021). In Gading Sari Village, Tapung, Riau Province, Oil palm farming has emerged as the principal source of income for the majority of residents, who are migrants from Java Island since 1991 (Aulia et al., 2020). However, the welfare of oil palm farmers remains uneven. Various factors influence this disparity, such as land ownership, number of family dependents, monthly income, additional income, education level, and other socioeconomic variables. Addressing these inequalities is crucial for inclusive development and sustainable rural economic growth. In addition to providing policy implications, the results of the clustering analysis in this study are also designed to be utilized in the field of education. The socio-economic clusters generated from the K-Means algorithm are employed as a foundation for developing student worksheets that are based on real and local data.

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Previous studies on the welfare of oil palm farmers have predominantly concentrated on macro-level analyses, such as the economic impacts of oil palm on national or regional scales (Mehraban et al., 2021). However, these studies tend to overlook micro-level socioeconomic factors among individual farmers. Additionally, welfare analyses often employ conventional statistical methods less capable of identifying heterogeneous patterns within the population (Nurfatriani et al., 2022). This study adopts a data mining approach using the K-Means Clustering algorithm to categorize farmers based on their welfare attributes (Ula et al., 2023; Ying et al., 2021).

This study aims to cluster oil palm farmers in Gading Sari Village using key variables: land area, number of family dependents, average monthly income, additional income, and education level. The data analysis employs the K-Means Clustering algorithm to identify groups of farmers with similar welfare characteristics (Khan et al., 2021). This method enables a more detailed welfare analysis, moving beyond simple categorizations such as "poor" or "wealthy" to reveal more complex stratifications.

The primary motivation for this study is to provide an analytical framework that the government can utilize for more targeted rural development strategies (Xin et al., 2022). Gading Sari Village was chosen as the case study because it represents a community highly dependent on oil palm farming. This research contributes to two significant aspects. First, it demonstrates the application of machine learning methods, particularly K-Means Clustering, in analyzing socioeconomic data within the agricultural context (Sinaga & Yang, 2020). Second, it provides empirical insights into the welfare stratification of oil palm farmers, identifying key factors driving disparities. The findings reveal three welfare clusters: low, medium, and high, with land area and average monthly income emerging as the main distinguishing factors.

This research provides an adaptable framework to understand micro-level welfare dynamics, offering insights into the factors that shape individual welfare, particularly for oil palm farmers. By integrating advanced analytical methods, such as machine learning and data clustering, the research offers both theoretical and empirical foundations to address welfare disparities. This approach can be applied in other regions to analyze similar issues. It is expected to provide data for policymakers to make more accurate, effective, and targeted decisions for sustainable development.

The socio-economic welfare of oil palm farmers in rural areas has become a significant research focus for several researchers. Most studies discuss economic sustainability at the macro level and national economic growth due to CPO exports (Siti-Dina et al., 2023). However, limited research has addressed the uneven welfare of oil palm farmers (Mulyasari et al., 2023). Previous studies have primarily focused on macroeconomic aspects, while somewhat neglecting the microeconomic factors of the oil palm industry (Bremer et al., 2022). Many variables can be explored, such as land ownership, number of family dependents, monthly income, supplementary income, education level, and other socioeconomic factors that influence the welfare of oil palm farmers.

Previous research has examined various factors that influence the welfare of oil palm farmers. It highlights that farmers with larger landholdings and additional income sources tend to achieve better living standards, while those with smaller land areas often struggle with economic difficulties (Dharmawan et al., 2020). Although these studies provide useful insights using traditional regression-based methods or other quantitative approaches, they tend to focus on broad trends (Purwanto et al., 2020). This approach often overlooks the unique circumstances and challenges faced by individual farmers, making it harder to understand the diversity and complexity within the farming community (Chrisendo et al., 2021). A more nuanced and human-centered analysis is needed to fully capture these dynamics and provide actionable insights.

According to several recent studies, the main focus on oil palm farmers has been the impact of CPO prices (Haykal & Yunus, 2021). Research utilizing clustering algorithms on oil palm farmers has centered on land size, number of trees, and production levels (Ula et al., 2023). Other studies examine the demographic policies of the central government regarding rural plantation development and their economic impact (Rustiadi et al., 2023). A particularly fascinating approach is using Principal Component Analysis (PCA) combined with Structural Equation Modeling (SEM) to delve deeper into how palm oil subsidies influence community welfare, uncovering direct impacts and underlying dynamics (Jingjing et al., 2024). Given these developments, it would be highly intriguing to explore the socioeconomic conditions of oil palm farmers using clustering algorithms (Herdiansyah et al., 2023). By applying clustering algorithms to the dataset in this study, the analysis can uncover existing disparities and the key drivers behind differences in welfare. This approach could generate new insights that can serve as a foundation for the government in formulating and implementing policies. This study's findings have been adapted into learning modules to teach students how to interpret clustering results in the context of agricultural sustainability, integrating scientific literacy and real-world data analysis in the science classroom.

Method

The aim of this study is to cluster the welfare levels of oil palm farmers in Gading Sari Village, Tapung, using the K-Means Clustering algorithm (Ahmed et al., 2020). The research methodology includes stages of data collection, data processing, cluster analysis, and result evaluation. Each stage is carefully executed to ensure that the findings are accurate and reliable.

Research Design

This study utilizes a quantitative approach with a descriptive design. The K-Means Clustering method is selected because it can identify hidden patterns in complex datasets without requiring prior knowledge of the group structure. This approach facilitates the mapping of the welfare levels of oil palm farmers based on relevant variables, such as land area, family dependents, average monthly income, additional income, and education level.

Population and Sample

The population of this study consists of all oil palm farmers in Gading Sari Village, Tapung in September 2024. A purposive sampling technique is employed to select farmers based on specific criteria: those actively involved in oil palm cultivation. One hundred eleven oil palm farmers are chosen as the sample. The sample is selected to represent a diverse range of farm sizes, educational levels, and economic conditions.

Data Collection

Primary data is gathered through face-to-face interviews with oil palm farmers, utilizing a structured questionnaire. The questionnaire is designed to gather information on five key variables relevant to the study: The land size owned by the oil palm farmers in hectares. The number of family members depends on the farmer, while the farmer's monthly income is generated from oil palm farming. Income earned by the farmer from sources other than oil palm farming. The highest level of education completed by the farmer.

Data Processing

After data collection, the next step is data preprocessing, which includes normalization of the data. Normalization is essential to prevent larger-scale variables from dominating the clustering process. The normalization is performed using the Min-Max Scaling method, which transforms the range of each variable to a scale between 0 and 1, ensuring that each variable carries equal weight in the clustering process. After normalization, 5 data points were identified as outliers. Therefore, for the clustering process, only 106 data points were used.

K-Means Clustering Analysis

At this stage, the K-Means Clustering algorithm is used to categorize the oil palm farmers based on the five selected variables. The optimal number of clusters is determined using the Elbow Method before applying the K-Means algorithm. This method helps identify the most appropriate number of clusters based on the A plot of the Within-Cluster Sum of Squared Errors (WSS) is generated against the number of clusters, enabling the identification of the optimal number of clusters that best capture the variation in farmers' welfare.

$$d(\mathbf{p},\mathbf{q}) = d(\mathbf{q},\mathbf{p}) = \sqrt{(q_1-p_1)^2 + (q_2-p_2)^2 + \cdots + (q_n-p_n)^2}$$
$$= \sqrt{\sum_{i=1}^{n}(q_i-p_i)^2}.$$

Figure 1. Euclidean Formula

Figure 1, the euclidean distance formula determines the direct distance between two points in an n n-dimensional space by finding the square root of the total sum of the squared differences between their corresponding coordinates. The larger the difference between the coordinates, the greater the distance (p,). After determining the optimal number of clusters, the K-Means algorithm is used to divide the data into distinct clusters. The clustering results will offer insights into groups of farmers categorized by low, medium, and high welfare levels, based on the factors affecting their welfare.

Data Analysis

The clustered results are analyzed to identify the main characteristics that distinguish each cluster, such as differences in land size, monthly income, and education level. This analysis explores the factors contributing to the variation in welfare among oil palm farmers. The findings will be used to provide policy recommendations to improve the welfare of farmers, focusing on enhancing access to resources, improving education, and optimizing income management. This research uses data mining software RapidMiner to analyze the data.

Conclusions and Recommendations

Based on the results of the clustering analysis and data evaluation, this study aims to offer a deeper understanding of the welfare conditions of oil palm farmers in Gading Sari Village. The policy recommendations derived from this study will focus on enhancing the welfare of farmers, tailored to the identified clusters, and taking into account the socio-economic conditions of each group. this research does not only serve as a data-driven policy framework but also as a pedagogical tool to support data literacy, interdisciplinary learning, and scientific inquiry in secondary school education.

Result and Discussion

This study seeks to comprehensively group the welfare levels of oil palm farmers in Gading Sari Village, Tapung, by utilizing the K-Means Clustering algorithm. The analysis considers five key variables: land area, number of family dependents, average monthly income, total income, and education level. Through this analysis, three main clusters of oil palm farmers were identified, categorized into low, medium, and high welfare levels.

Table 1 is the dataset used in the study, which contains various variables related to the welfare of oil palm farmers in Gading Sari Village, Tapung. The dataset includes key factors such as land area, number of family dependents, average monthly income, total income, and education level. These variables were analyzed to identify clusters representing different welfare levels among the farmers. The data serves as the foundation for applying the K-Means Clustering algorithm to classify farmers into distinct groups based on their socio-economic conditions.

Table 1. Dataset of Oil Palm Farmers in Gading Sari Village

No	Id	Education	Family Dependents	Land Area (ha)	Monthly Average	Total income
1	2409180102	5	4	2	17.5	17.5
2	2409180103	1	5	6	10.25	20.5
3	2409180104	3	4	4	12.625	37.875
4	2409190105	5	5	6	27.6	110.4
5	2409190106	5	4	5	18.25	91.25
:	:	:	:	:	:	:
105	2409201109	5	2	2	20.5	2152.5
106	2409201110	3	5	4	20	2120

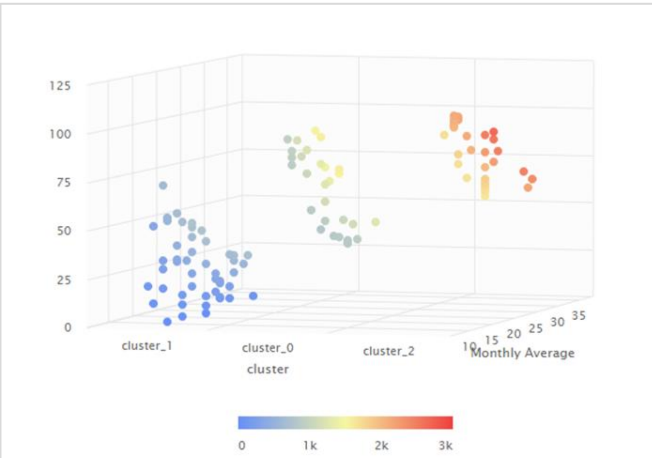

Figure 2. Clastering Result

Figure 2 presents the results of clustering the research data using the RapidMiner application. From the figure, the results clearly distinguish between Cluster 0, Cluster 1, and Cluster 2. Cluster 0 consists of 28 items, indicating that this group has the smallest proportion compared to the other clusters. Cluster 1 consists of 48 items, making it the largest cluster, which may indicate more dominant characteristics in the data. Cluster 2 consists of 30 items, falling between Cluster 0 and Cluster 1 in terms of the number of items.

Table 2, provides a descriptive comparison of three clusters based on several attributes: Education, Family Dependents, Land Area (ha), Monthly Average, and Total Income. In terms of Education, the three clusters show relatively similar levels. Cluster 1 has the highest education average at 3.625, followed by Cluster 2 at 3.200 and Cluster 0 at 3.107.

Table 2. Descriptive Comparison of Clusters

Attribute	Cluster-0	Cluster-1	Cluster-2
Education	3.107	3.625	3.200
Family Dependents	3.714	3.833	4
Land Area (ha)	2.500	2.792	3.633
Monthly Average	17.786	16.104	25.667
Total income	1115.679	387.062	2039.133

For Family Dependents, Cluster 2 has the most significant household size, averaging four family members, while Cluster 1 and Cluster 0 have slightly smaller averages at 3.833 and 3.714, respectively. Regarding Land Area, Cluster 2 possesses the largest average land area, with 3.633 hectares, compared to 2.792 hectares in Cluster 1 and 2.500 hectares in Cluster 0. When looking at monthly average income, Cluster 2 has the highest earnings at 25.667, which is significantly higher than Cluster 0, with 17.786, and Cluster 1, which records the lowest average at 16.104.

The Total Income further highlights the economic disparity between the clusters. Cluster 2 stands out with the highest total income of 2039.133, indicating superior economic conditions. Cluster 0 follows at 1115.679, while

Cluster 1 lags far behind with the lowest total income at 387.062.

Based on the data analysis divided into three clusters, significant differences were found in the attributes of Education, Family Dependents, Land Area (ha), Monthly Average Income, and Total Income. This discussion aims to understand the patterns emerging from each cluster and the factors influencing the welfare of farmers in the study area.

Cluster 2: The Group with the Highest Welfare. Cluster 2 shows the highest economic indicators compared to the other clusters, with the highest monthly income (25,667) and total income of 2039.133. This is supported by the largest land area (3.633 ha) and the most significant number of family dependents (4 people). The larger land area provides more significant productivity potential, which directly contributes to the higher total income of this group. Furthermore, the more substantial number of dependents might indicate better utilization of household labour to manage agricultural land efficiently. Although the education level in this cluster is not the highest (3.200), the primary factor contributing to this group's welfare appears to be the utilization of larger land areas and effective household economic strategies. This underscores the importance of land access as a key factor in improving the income of farmers.

Cluster 1: The Group with the Lowest Welfare In contrast to Cluster 2, Cluster 1 has the lowest monthly income (16,104) and the most minor total income (387,062). Interestingly, this group has the highest average education level (3.625) among the three clusters. However, a higher level of education does not necessarily correlate with higher income. This suggests that while education is essential, it has yet to be effectively translated into higher earnings. Additionally, the land area of this group is smaller (2.792 ha) compared to Cluster 2, indicating that land limitation is a significant constraint to increasing income. The lower productivity resulting from limited land and the less optimal use of available resources may explain the dominant low-income status of this group.

Cluster 0: The Group with Intermediate Welfare. Cluster 0 lies between Cluster 1 and Cluster 2 in most attributes. Total income (1115.679) and monthly income (17.786) reflect a better economic status than Cluster 1 but still fall far below Cluster 2. This group has an average land area of 2.500 ha, which is smaller than Cluster 2 but still sufficient to support stable agricultural productivity. With an average education level of 3.107 and family dependents of 3.714, Cluster 0 reflects a middle-income group, where land and income factors seem to influence each other.

The findings provide several key insights: Land Area as a Primary Factor: Larger land areas enable higher productivity, as seen in Cluster 2. Governments or relevant stakeholders should consider policies for land redistribution or more effective land use to improve farmers' welfare. Optimization of Education: Cluster 1 shows that higher education does not necessarily correlate with higher income. This suggests the need for training and the application of modern technologies to increase productivity and farmer incomes.

Strengthening Household Economic Strategies: Cluster 2 shows that a larger family size can be optimized to increase land productivity, either through family labour involvement or better resource management strategies. Cluster 2 stands out as the group with the highest welfare, supported by larger land areas and effective household strategies. On the other hand, Cluster 1, despite having the highest education level, faces significant economic challenges due to land constraints. Meanwhile, Cluster 0 represents a middle ground with stable economic characteristics but still needs to be optimized.

Conclusion

The analysis of data based on the clustering of oil palm farmers in Gading Sari Village provides valuable insights into the factors that influence their welfare. The three clusters, each with unique characteristics, reveal that land area, family dependents, and income levels are key determinants of welfare. Cluster 2 represents the group with the highest economic welfare, mainly due to having a larger land area, higher total income, and practical household economic strategies. While education levels are not the highest, the availability of more land and efficient use of family labour are major contributors to their success. Cluster 1 has the highest educational level but faces economic difficulties, with the lowest total income and smaller land area. This suggests that more than education alone is needed to guarantee better financial outcomes, and other factors, such as limited access to land and suboptimal resource use, need to be addressed. Cluster 0 is positioned in between, with moderate income and land area, representing a middle-income group. While this cluster has relatively stable attributes, there is potential for improvement in land use optimization and income enhancement through education and technology. This study emphasizes the critical role of land access in improving farmers' welfare and the need for more potent household economic strategies. It also shows that education by itself is only sufficient to improve economic conditions with adequate resources such as land and technology. Future policy measures should focus on increasing land access, offering agricultural training, and promoting efficient land management practices to improve the welfare of farmers in Gading Sari Village. Beyond the implications for policymaking, the findings of this study have also been tested in the context of educational innovation. Clustering results were utilized in trial-based classroom learning in senior high schools to demonstrate how real socio-economic data can be integrated into science education. These trials adopted a project-based learning model, enabling students to explore local issues using analytical tools such as K-Means clustering

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Conceptualization: F.K.O.; methodology: Z.; validation: A.N. A.; formal analysis: N.; investigation: A.P.; resources: F.K.O.; data curation: Z.; writing—original draft preparation: F. K. O.; writing—review and editing: A.A.A.; visualization: N.; All authors have read and agreed to the published version of the manuscript.

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Conflicts of Interest
The authors declare no conflict of interest.

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