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IMPLEMENTATION OF A WEB-BASED DECISION TREE MODEL FOR CLASSIFICATION OF MOBILE GAME ADDICTION POTENTIAL BASED ON DURATION, FREQUENCY, AND SLEEP PATTERN

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ABSTRACT

The rapid growth of mobile gaming has increased playing duration and frequency among users, potentially affecting sleep patterns and leading to addictive behavior. Early identification of mobile game addiction is important to help users recognize unhealthy gaming habits. This study aims to develop a web-based classification system for detecting mobile game addiction potential using the Decision Tree (C4.5) algorithm. The classification process is based on three indicators: playing duration, playing frequency, and sleep patterns. A dataset consisting of 19 active mobile game users was collected and processed using entropy and information gain calculations to generate classification rules and construct a decision tree model. The system classifies users into three categories: mild, moderate, and severe addiction potential. The results showed that Playing Duration produced the highest Information Gain value (1.038) and was selected as the root node of the decision tree. System testing demonstrated that all evaluated testing samples were classified correctly, resulting in an accuracy of 100% for the tested samples. The developed web-based system provides clear and interpretable classification results and can support the early identification of mobile game addiction potential based on user gaming behavior.

INTRODUCTION

The rapid advancement of digital technology has significantly transformed entertainment activities, particularly through the widespread adoption of mobile games. With the increasing availability of smartphones and internet access, mobile games have become one of the most popular forms of digital entertainment among students and young adults. Popular titles such as Mobile Legends, Free Fire, and Roblox attract millions of active users due to their accessibility, competitive gameplay, and interactive features. While mobile gaming offers recreational benefits, excessive engagement may lead to behavioral problems that affect users' daily activities.

Excessive mobile game usage is often associated with prolonged playing duration, high playing frequency, and disrupted sleep patterns. These factors may negatively affect physical health, psychological well-being, academic performance, and social interactions. Individuals who spend extended periods playing mobile games frequently experience reduced sleep quality, fatigue, and decreased concentration during daily activities. Consequently, early identification of addiction-related behavior has become an important concern in both educational and technological contexts.

Previous studies have primarily focused on examining the relationship between gaming behavior and addiction through survey-based approaches and questionnaire analysis. However, limited research has integrated playing duration, playing frequency, and sleep patterns into a web-based classification system capable of automatically identifying the potential level of mobile game addiction. This limitation indicates the need for a practical and accessible technological solution that can assist users in recognizing unhealthy gaming habits at an early stage.

To address this issue, this study implements the Decision Tree (C4.5) algorithm as a classification method for identifying mobile game addiction potential. The algorithm was selected because it is simple, interpretable, and capable of generating classification rules through entropy and information gain calculations. Furthermore, the resulting decision tree provides a transparent decision-making process that can be easily understood by users and system administrators.

The novelty of this study lies in the integration of three behavioral indicators, namely playing duration, playing frequency, and sleep patterns, into a web-based classification system using the Decision Tree (C4.5) algorithm. Unlike previous studies that primarily relied on questionnaire analysis and statistical approaches, this research implements an automated classification model capable of providing real-time identification of mobile game addiction potential. The resulting system offers a practical tool for early detection and supports users in understanding their gaming behavior through interpretable decision-making rules.

Therefore, this study aims to develop a web-based classification system that utilizes the Decision Tree (C4.5) algorithm to classify mobile game addiction potential based on playing duration, playing frequency, and sleep patterns. The proposed system is expected to support the early identification of addiction potential and provide users with a clearer understanding of their gaming behavior.

RESEARCH METHODS

Data Collection

Data collection was conducted using two methods: literature study and questionnaire distribution. The literature study was performed by reviewing books, scientific journals, conference papers, and other relevant publications related to mobile game addiction, Decision Tree (C4.5), web-based systems, playing duration, playing frequency, and sleep patterns. This stage provided the theoretical foundation for identifying the variables and classification criteria used in this study.

The primary data were collected through questionnaires distributed to active mobile game users. The questionnaire was designed to gather information regarding respondents' gaming behavior, including playing duration, playing frequency, and sleep patterns. These variables were selected because they are commonly associated with indicators of mobile game addiction.

The collected data were subsequently processed and categorized into predefined classification classes. The resulting dataset served as the basis for constructing the Decision Tree (C4.5) model and generating classification rules for identifying mobile game addiction potential.

Dataset Description

The dataset used in this study consisted of 19 respondents who were active mobile game users. The data were obtained through questionnaire responses and were used as training data for the Decision Tree (C4.5) classification process. Each respondent was evaluated based on three behavioral indicators associated with mobile game addiction.

The classification attributes included playing duration, playing frequency, and sleep patterns. Playing duration represents the average amount of time spent playing mobile games per day, while playing frequency indicates the number of days spent playing games within a week. Sleep patterns were used to assess the respondents' daily sleeping duration and its potential relationship with gaming behavior.

Based on these attributes, respondents were categorized into three addiction potential classes: Mild, Moderate, and Severe. These classes served as the target variables for the Decision Tree (C4.5) classification model.

Table 1. Classification Attributes Used in the Decision Tree

No	Attribute	Description
1	Playing Duration	Average daily gaming duration
2	Playing Frequency	Number of gaming days per week
3	Sleep Patterns	Average daily sleeping duration
4	Classification	Mild, Moderate, Severe

Decision Tree (C4.5) Implementation

The Decision Tree (C4.5) algorithm was implemented to classify mobile game addiction potential based on three behavioral indicators: playing duration, playing frequency, and sleep patterns. The algorithm was selected because it is capable of generating classification rules in the form of a decision tree that is easy to understand and interpret. Through this approach, users can be classified into three addiction potential categories: Mild, Moderate, and Severe.

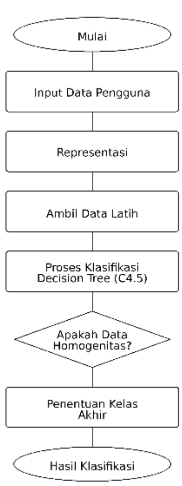

Figure 1. Decision Tree Classification Process

Figure 1 illustrates the workflow of the Decision Tree (C4.5) classification process, beginning with user data input, followed by entropy and information gain calculations, root node selection, decision tree construction, and ending with the generation of classification results.

The classification process begins by calculating the entropy value of the dataset. Entropy is used to measure the level of uncertainty within the data and determine the distribution of classes in the dataset. The entropy formula used in this study is presented as follows:

$$Entropy(S) = -\sum_{i=1}^{n} p_i \log_2(p_i)$$

where p_i represents the probability of each class in the dataset.

After calculating entropy, the Information Gain value is computed for each attribute. Information Gain is used to identify the attribute that contributes the most to reducing uncertainty and improving classification performance. The attribute with the highest Information Gain value is selected as the root node of the decision tree. The Information Gain formula is expressed as follows:

$$Gain(S, A) = Entropy(S) - \sum_{v \in Values(A)} \frac{|S_v|}{|S|} \times Entropy(S_v)$$

where A represents an attribute, S represents the entire dataset, and S_v denotes the subset of data associated with a particular attribute value.

Table 2. Decision Tree Classification Parameters

No	Attribute	Description
1	Playing Duration	Average daily gaming duration
2	Playing Frequency	Number of gaming days per week
3	Sleep Patterns	Average sleeping duration per day
4	Entropy	Measure of data uncertainty
5	Information Gain	Attribute selection criterion
6	Classification Result	Mild, Moderate, Severe

Web Development Environment

The web-based classification system was developed using PHP Native version 8.0.30 as the primary programming language and MySQL as the database management system. The system was implemented to process user input data, perform Decision Tree (C4.5) classification, and generate mobile game addiction potential results automatically.

XAMPP Control Panel version 3.3.0 was utilized as the local server environment to support application development and testing. Database administration activities were conducted using phpMyAdmin version 5.2.1, while Visual Studio Code was employed as the main source code editor throughout the development process.

The integration of these technologies enabled the development of a lightweight, accessible, and user-friendly web-based classification system capable of processing user data and generating classification results efficiently.

Table 3. Software Development Tools

No	Software	Version
1	PHP Native	8.0.30
2	MariaDB	10.4.32
3	XAMPP Control Panel	3.3.0
4	phpMyAdmin	5.2.1
5	Visual Studio Code	1.123.0

RESULTS AND DISCUSSION

Dataset Distribution

The dataset used in this study consisted of 19 respondents who were active mobile game users. The data were collected through questionnaires and categorized into three addiction potential classes: Mild, Moderate, and Severe. The classification was determined based on three behavioral attributes, namely playing duration, playing frequency, and sleep patterns.

The distribution of respondents across the three classification categories is presented in Table 4. This distribution provides an overview of the dataset composition and serves as the foundation for the Decision Tree (C4.5) classification process. Understanding the distribution of classes is important because it influences entropy calculations, information gain values, and the resulting decision tree structure.

Table 4. Distribution of Addiction Potential Classes

No	Classification	Total
1	Mild	1
2	Moderate	10
3	Severe	8
4	Total	19

Entropy Calculation

Entropy was calculated to measure the level of uncertainty within the dataset and to evaluate the capability of each attribute in separating the addiction potential classes. In the Decision Tree (C4.5) algorithm, attributes with lower entropy values generally indicate a greater ability to produce homogeneous classifications, making them more suitable for decision tree construction. The entropy value was calculated using the following equation:

$$Entropy(S) = -\sum_{i=1}^{n} p_i \log_2(p_i)$$

The entropy value was calculated using the equation presented above to evaluate the level of uncertainty associated with each attribute. Entropy analysis plays an important role in the Decision Tree (C4.5) algorithm because it helps determine how effectively an attribute can separate data into homogeneous classes. Attributes with lower entropy values indicate a better capability to reduce uncertainty and improve the classification process. The resulting entropy values for all evaluated attributes are presented in Table 5.

Table 5. Entropy Calculation Results

No	Attribute	Entropy
1	Playing Duration	0.528
2	Sleep Patterns	1.295
3	Playing Frequency	1.211

Based on Table 5, the Playing Duration attribute produced the lowest entropy value (0.528), indicating a higher capability to separate the dataset into more homogeneous classes. In contrast, Sleep Patterns and Playing Frequency generated higher entropy values, reflecting greater uncertainty in distinguishing addiction potential categories. These findings suggest that playing duration contributes more significantly to the classification process than the other evaluated attributes.

Information Gain Calculation

Information Gain was calculated to determine the most informative attribute for constructing the Decision Tree (C4.5) model. This metric measures the reduction in entropy achieved after partitioning the dataset based on a specific attribute. Attributes with higher Information Gain values provide better separation of classes and are therefore preferred during decision tree construction.

$$Gain(S, A) = Entropy(S) - \sum_{v \in Values(A)} \frac{|S_v|}{|S|} \times Entropy(S_v)$$

The Information Gain calculation was performed for all classification attributes to identify the attribute that contributed the most to reducing dataset uncertainty. Attributes with higher Information Gain values indicate a stronger capability to distinguish addiction potential categories and improve classification performance. The resulting Information Gain values for all evaluated attributes are presented in Table 6.

Table 6. Information Gain Results

No	Attribute	Information Gain
1	Playing Duration	1.038
2	Playing Frequency	0.355
3	Sleep Patterns	0.271

Based on Table 6, Playing Duration produced the highest Information Gain value of 1.038, indicating the strongest ability to reduce dataset uncertainty and separate respondents into distinct addiction potential categories. Compared to Playing Frequency (0.355) and Sleep Patterns (0.271), Playing Duration contributed the most to the classification process. Therefore, Playing Duration was selected as the root node of the Decision Tree (C4.5) model. This finding suggests that the amount of time spent playing mobile games is the most influential factor in determining the level of mobile game addiction potential among respondents.

Decision Tree Formation

Based on the entropy and Information Gain calculations, Playing Duration produced the highest Information Gain value and was therefore selected as the root node of the Decision Tree (C4.5) model. The decision tree was constructed recursively by selecting the attribute with the highest Information Gain value at each node until all records were classified into homogeneous classes.

The resulting decision tree represents the classification rules used to determine the addiction potential level of mobile game users based on playing duration, playing frequency, and sleep patterns. These rules enable the system to automatically classify users into Mild, Moderate, or Severe categories according to their behavioral characteristics.

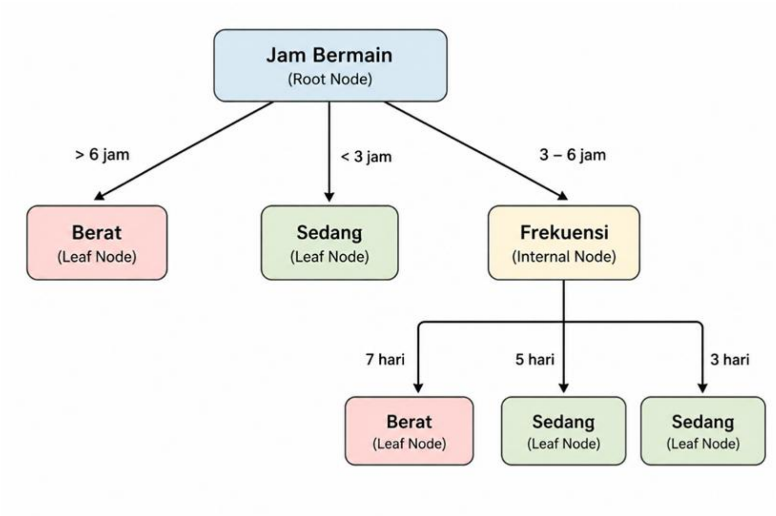

Figure 2. Final Decision Tree Structure

Figure 2 presents the final Decision Tree (C4.5) model generated from the dataset. Playing Duration was selected as the root node because it produced the highest Information Gain value. The resulting tree shows that playing duration is the primary factor influencing addiction potential classification, while playing frequency acts as a secondary decision attribute for respondents with a playing duration between 3 and 6 hours per day.

1. If Playing Duration is greater than 6 hours per day, then the classification result is Severe.
2. If Playing Duration is less than 3 hours per day, then the classification result is Moderate.
3. If Playing Duration is between 3 and 6 hours per day and Playing Frequency is 7 days per week, then the classification result is Severe.
4. If Playing Duration is between 3 and 6 hours per day and Playing Frequency is 5 days per week, then the classification result is Moderate.
5. If Playing Duration is between 3 and 6 hours per day and Playing Frequency is 3 days per week, then the classification result is Moderate.

The above rules were automatically applied by the system to classify user data and determine the corresponding addiction potential category.

System Implementation

The Decision Tree (C4.5) model was implemented in a web-based application developed using PHP Native and MariaDB. The system was designed to facilitate the classification of mobile game addiction potential by allowing users to input behavioral data and obtain classification results automatically. The implementation consists of a user input interface and a classification result interface.

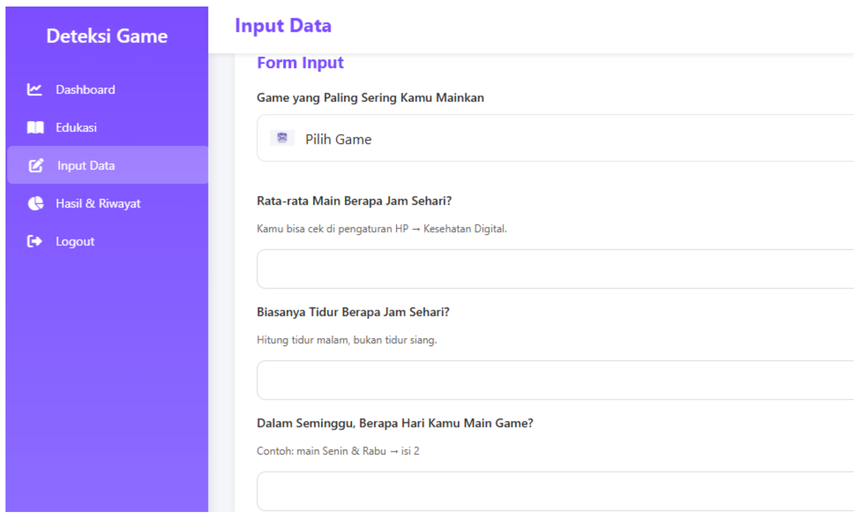

Figure 3. Mobile Game Addiction Data Input Interface

Figure 3 illustrates the user input interface used to collect classification attributes from respondents. The form requires users to provide information regarding playing duration, playing frequency, and sleep patterns. These attributes serve as the primary input variables for the Decision Tree (C4.5) classification process. After the required data are entered, the system processes the information and prepares it for classification.

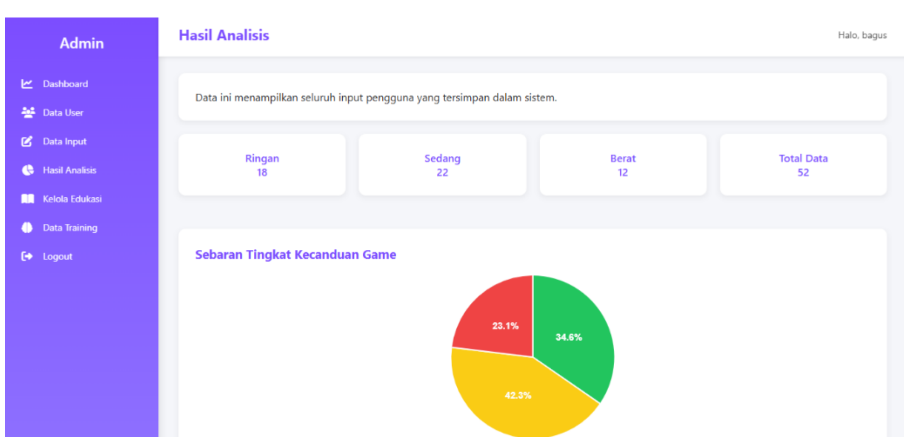

Figure 4. Addiction Potential Classification Results Dashboard

Figure 4 presents the classification result interface of the developed web application. The system displays the distribution of addiction potential categories and provides a summary of classification outcomes generated using the Decision Tree (C4.5) model. The visualization enables administrators to monitor classification results and analyze the distribution of user addiction potential levels effectively.

The implementation demonstrates that the developed web-based system is capable of integrating the Decision Tree (C4.5) algorithm into a practical application. By automating the classification process and presenting the results through an interactive interface, the system enables efficient classification and supports the analysis of mobile game addiction potential among users.

System Testing

The developed web-based classification system was tested using respondent data to evaluate the correctness of the implemented Decision Tree (C4.5) model. The testing process compared the classification results generated by the system with the expected classifications obtained from the decision tree rules.

Table 7 presents several testing samples used to verify the consistency of the classification process. The results show that the system successfully classified respondents into Mild, Moderate, and Severe addiction potential categories according to the predefined decision rules.

Table 7. Classification Testing Results

No	Playing Duration	Sleep Patterns	Playing Frequency	Expected Class	System Result
1	< 3 Hours	> 6 Hours	3 Days	Moderate	Moderate
2	3–6 Hours	4–6 Hours	5 Days	Moderate	Moderate
3	> 6 Hours	≤ 4 Hours	7 Days	Severe	Severe
4	3–6 Hours	> 6 Hours	3 Days	Moderate	Moderate
5	> 6 Hours	4–6 Hours	7 Days	Severe	Severe

The testing results indicate that the implemented Decision Tree (C4.5) model was able to classify user data correctly according to the established decision rules. All tested samples produced classification outcomes that matched the expected classes, resulting in an accuracy of 100% for the evaluated testing samples. These findings confirm that the developed web-based system can effectively support the identification of mobile game addiction potential based on playing duration, sleep patterns, and playing frequency.

Limitations

This study has several limitations. First, the dataset used in this research consisted of only 19 respondents, which may limit the generalizability of the classification results to a broader population of mobile game users. A larger dataset could provide more representative patterns and improve the reliability of the Decision Tree (C4.5) model.

Second, the classification process was based solely on three behavioral indicators, namely playing duration, playing frequency, and sleep patterns. Although these variables are closely related to mobile game addiction behavior, other potentially influential factors such as academic performance, emotional condition, social interaction, and psychological characteristics were not included in the analysis.

Third, the evaluation of the developed system was limited to testing based on predefined classification rules and sample respondent data. More comprehensive validation using larger datasets and additional performance metrics could provide a more accurate assessment of the model's effectiveness.

Therefore, future studies are recommended to involve a larger number of respondents, incorporate additional behavioral and psychological variables, and apply more extensive evaluation methods to improve the robustness and generalizability of the classification model.

CONCLUSION

This study successfully developed a web-based classification system for identifying the potential level of mobile game addiction using the Decision Tree (C4.5) algorithm. The classification process was performed based on three behavioral attributes, namely playing duration, playing frequency, and sleep patterns. The implementation of the algorithm enabled the system to automatically classify users into Mild, Moderate, and Severe addiction potential categories through a transparent and interpretable decision-making process.

The results showed that Playing Duration produced the highest Information Gain value (1.038) and was selected as the root node of the decision tree. The generated decision tree structure effectively represented the relationship between user behavioral patterns and mobile game addiction potential levels. Furthermore, system testing demonstrated that all evaluated testing samples were classified correctly according to the predefined decision rules, resulting in an accuracy of 100% for the tested samples.

Overall, the proposed system can serve as an effective tool for the early identification of mobile game addiction potential. By utilizing user behavioral data, the system provides a simple and accessible approach to support awareness and monitoring of gaming habits among mobile game users. However, the findings are limited by the relatively small dataset size and should be further validated using larger and more diverse respondent data in future studies.

REFERENCES

Diana, & Putra, A. (2021). Aplikasi pengelolaan dokumen digital berbasis web dan Android. *InfoTekJar: Jurnal Nasional Informatika dan Teknologi Jaringan*, 6(1), 165–172.

Dwi Setiyawan, R., Hermawan, D., Alfiansyah, M. S., Wirapraja, M. N. K., & Yuliana. (2024). Pengenalan Database Management System (DBMS*). Jurnal Kajian Komputasi Inovatif*, 15(1), 30–33.

Elna Y. Siregar, & Rodiatul H. Siregar. (2013). Penerapan Cognitive Behavior Therapy (CBT) terhadap pengurangan durasi bermain games pada individu yang mengalami games addiction. *Jurnal Psikologi UIN Sultan Syarif Kasim Riau,* 9, 17–24.

Erin Padilla Siregar. (2024). Hubungan kecanduan game online dengan pola tidur. *Motorik Jurnal Kesehatan*, 17(6), 13–18.

Fauzi, F., & Rusli, D. (2024). The relationship between addiction to the online game Mobile Legends Bang-Bang (MLBB) and sleep quality in teenagers. *Jurnal Psikologi Teori dan Terapan*, 15(2), 218–228.

Handriana, I., Wati, E., & Amelia, D. (2021). Hubungan kebiasaan bermain game online dengan pola tidur pada remaja. *Jurnal Kesehatan*, 9(2), 168–179.

Hanik, U., Nurjanah, S., Sari, R. Y., Faizah, I., & Rohmawati, R. (2023). Does game addiction have a relationship with adolescent sleep quality? Bali Medical Journal, 12(3), 2812–2814.

Hakim, D. S., & Widodo, A. (2023). Hubungan kecanduan game online terhadap pola tidur pada remaja. *Jurnal Kesehatan Tambusai*, 6(2), 417–421.

Haviluddin. (2011). Memahami penggunaan UML (Unified Modeling Language). *Jurnal Informatika Mulawarman*, 6(1), 1–15.

Kurniasih, E. (2022). Perilaku bermain game online dengan pola tidur remaja: Studi korelasi. *Jurnal Profesi Kesehatan Masyarakat* (JPKM), 3(2), 77–85.

Mukhlis, I. R., & Santoso, R. (2023). Perancangan basis data perpustakaan universitas menggunakan MySQL dengan Physical Data Model dan Entity Relationship Diagram. *Journal of Technology and Informatics* (JoTI), 4(2), 81–87.

Mulyani, U., & Fitriani, W. (2022). Emosi remaja kecanduan game online Mobile Legends. *JCOSE: Jurnal Bimbingan dan Konseling*, 5(1), 29–35.

Nawawi, I., & Fatah, Z. (2024). Penerapan Decision Tree dalam mendeteksi pola tidur sehat berdasarkan kebiasaan gaya hidup. *Jurnal Ilmiah Sains Teknologi dan Informasi*, 2(4), 34–41.

Pebrianto, J. (2022). Perbandingan kecepatan baca dan tulis data pada MySQL menggunakan Primary Key Auto Increment dengan Universally Unique Identifier (UUID). *Media Jurnal Informatika,* 14(2), 86–93.

Poli, S. L., Kairupan, B. H. R., & Rahman, A. (2021). Kebiasaan bermain online games dengan kualitas tidur pada mahasiswa. *KESMAS: Jurnal Kesehatan Masyarakat*