

Explainable Data-Driven Machine Learning for Identifying MBG Program Beneficiaries in Medan City

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
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ABSTRACT

The effectiveness of social assistance programs depends heavily on the accuracy and transparency of beneficiary identification. In many urban areas, including Medan, challenges such as incomplete data, administrative bias, and inefficient targeting often lead to inclusion and exclusion errors in determining beneficiaries of the MBG (Makan Bergizi Gratis) program. This study aims to develop an explainable data-driven machine learning model to improve the accuracy and transparency of identifying eligible MBG program beneficiaries. The research employs a quantitative approach using socio-economic and demographic datasets collected from local government records, including variables such as household income, employment status, education level, household size, housing conditions, and access to public services. Several machine learning algorithms, including Random Forest, Gradient Boosting, and Logistic Regression, are implemented to classify potential beneficiaries. To enhance transparency and interpretability, the model integrates Explainable Artificial Intelligence (XAI) techniques, such as SHAP (Shapley Additive Explanations), to identify the most influential factors affecting eligibility predictions. The results demonstrate that the proposed data-driven model significantly improves the accuracy of beneficiary classification while providing interpretable insights into key socio-economic indicators influencing eligibility. The findings indicate that income level, employment status, household dependency ratio, and housing conditions are among the most critical determinants in identifying eligible recipients. The implementation of explainable machine learning models supports more transparent and accountable decision-making in social assistance programs. This research contributes to the development of data-driven governance by providing a robust analytical framework for improving the targeting efficiency of social welfare programs in urban areas. Practically, the proposed framework can assist policymakers and local government agencies in designing fairer and more efficient beneficiary identification systems for the MBG program in Medan City, ultimately supporting better resource allocation and improved social welfare outcomes.

Keywords: Data-driven machine learning; Explainable AI (XAI); MBG program beneficiaries; social assistance targeting; urban data analytics; Medan.

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1. INTRODUCTION.

The rapid development of digital technologies and data analytics has significantly transformed the way governments design and implement public policies, particularly in the management of social assistance programs. In recent years, the concept of **data-driven governance** has emerged as a strategic approach to improve the efficiency, transparency, and accountability of public service delivery. Governments increasingly rely on large-scale data analysis and intelligent systems to support decision-making processes and ensure that social programs reach the intended beneficiaries. According to World Bank (2021), data-driven approaches in public administration can enhance the accuracy of policy targeting and improve the effectiveness of welfare programs by utilizing integrated socio-economic datasets. However, many developing regions still face challenges related to incomplete data integration, administrative inefficiencies, and limited analytical capacity in managing social assistance distribution.

One of the major challenges in implementing social welfare policies is the accurate identification of eligible beneficiaries. Errors in beneficiary targeting often occur due to outdated household data, subjective decision-making processes, and fragmented information systems. These

issues can lead to inclusion errors, where ineligible households receive assistance, and exclusion errors, where vulnerable households fail to receive support. Such problems reduce the effectiveness of social programs and may undermine public trust in government policies. Therefore, improving the accuracy and transparency of beneficiary identification has become a critical priority for policymakers and local governments. In Indonesia, the government has introduced several social welfare programs aimed at improving the well-being of vulnerable populations. One of the emerging initiatives is the MBG (Makan Bergizi Gratis) program, which focuses on providing nutritional support and improving food security for communities in need. The success of this program largely depends on the ability of government institutions to identify eligible beneficiaries accurately and efficiently. In large urban areas such as Medan, this task becomes more complex due to population density, socio-economic diversity, and rapid urban development. As one of the largest cities in Indonesia, Medan experiences significant economic disparities across different neighborhoods, making it challenging to determine which households are most eligible for social assistance programs.

Traditional approaches for identifying beneficiaries typically rely on manual surveys, administrative records, and local verification processes conducted by government officers or community leaders. While these methods provide essential information, they are often time-consuming and may not effectively capture the complex socio-economic conditions of urban populations. Moreover, manual evaluation processes increase the risk of human error and subjective judgments in determining eligibility. According to Pedro Domingos (2015), traditional statistical methods often struggle to analyze large and complex datasets, whereas machine learning algorithms can uncover hidden patterns and relationships that improve predictive accuracy. Machine learning techniques have therefore become increasingly important in supporting data-driven decision-making within public sector institutions. By analyzing large volumes of socio-economic and demographic data, machine learning models can identify patterns that indicate which households are most likely to qualify for social assistance programs. Algorithms such as Random Forest, Logistic Regression, and Gradient Boosting have been widely applied in predictive classification problems, including poverty identification and social policy targeting (James et al., 2021). These models enable policymakers to process complex datasets and generate predictions with higher accuracy compared to traditional approaches.

Despite these advantages, the application of machine learning in public policy raises important concerns related to model transparency and interpretability. Many advanced algorithms operate as “black-box” models, meaning that their internal decision-making processes are difficult to understand. This lack of transparency can create challenges for government institutions, particularly when decisions related to social assistance eligibility must be explained to stakeholders and the public. According to Cynthia Rudin (2019), interpretable machine learning models are essential in high-stakes decision-making environments such as healthcare, finance, and public policy, where transparency and accountability are critical. To address these challenges, researchers have developed Explainable Artificial Intelligence (XAI) techniques that enable machine learning models to provide interpretable explanations for their predictions. Explainable AI methods, such as SHAP (Shapley Additive Explanations) and LIME (Local Interpretable Model-Agnostic Explanations), allow analysts to identify the most influential variables that contribute to prediction outcomes (Molnar, 2022). By integrating explainable techniques into machine learning models, policymakers can better understand how socio-economic indicators influence eligibility decisions. This transparency enhances trust in automated decision systems and supports fairer policy implementation. In the context of urban governance, combining data-driven machine learning with explainable AI offers significant opportunities to improve the targeting accuracy of social assistance programs. Socio-economic variables such as household income, employment status, education level, housing conditions, and family size can be analyzed simultaneously to determine eligibility probabilities for social assistance. This analytical approach supports the development of evidence-based policy decisions, allowing governments to allocate resources more efficiently and effectively. Furthermore, explainable models provide insights into the key determinants of social vulnerability, which can inform broader poverty reduction strategies.

Despite the increasing global adoption of data-driven governance, empirical research applying explainable machine learning models for social assistance targeting remains limited in Indonesia, particularly at the municipal level. Cities such as Medan require innovative approaches to improve the management of social welfare programs due to the complexity of their socio-economic structures. Therefore, this study aims to develop an Explainable Data-Driven Machine Learning model for

identifying eligible beneficiaries of the MBG program in Medan City. The proposed framework integrates predictive machine learning algorithms with explainable artificial intelligence techniques to enhance both the accuracy and transparency of beneficiary identification. By providing interpretable insights into the socio-economic factors influencing eligibility, the model is expected to support more effective policy decisions and improve the implementation of social assistance programs in urban environments.

2. LITERATURE REVIEW.

2.1. Data-Driven Governance in Social Assistance Programs

The concept of data-driven governance has emerged as a strategic approach for improving public sector decision-making by utilizing large datasets and analytical tools. Governments increasingly rely on data analytics and machine learning technologies to enhance the accuracy and efficiency of public service delivery, particularly in social welfare programs. Data-driven systems enable policymakers to analyze socio-economic indicators, predict vulnerability levels, and allocate resources more effectively. According to the World Bank, the integration of data analytics in public administration can improve targeting accuracy and reduce inefficiencies in social assistance programs.

Traditional approaches to identifying beneficiaries often rely on manual surveys and administrative records. However, these methods may lead to inaccurate targeting due to incomplete data and subjective decision-making processes. As a result, many welfare programs experience inclusion errors and exclusion errors, where ineligible households receive benefits while eligible households are overlooked. The use of predictive analytics and machine learning techniques has therefore been proposed as a solution to improve beneficiary identification and policy implementation efficiency. In developing countries, the challenge of identifying vulnerable households is even more complex due to demographic diversity, rapid urbanization, and socio-economic inequality. Urban areas require more advanced analytical frameworks to manage large-scale data related to poverty, employment, education, and household welfare. Consequently, data-driven decision systems have become essential tools for supporting evidence-based policymaking and improving the effectiveness of social welfare programs.

2.2. Machine Learning for Social Welfare Targeting

Machine learning is a branch of artificial intelligence that enables computers to learn patterns from data and generate predictions or classifications. In the context of social welfare policies, machine learning models can analyze multidimensional household data and determine eligibility probabilities for social assistance programs. Compared to traditional statistical approaches, machine learning techniques can process large datasets and uncover hidden relationships among socio-economic variables. Recent studies have demonstrated the effectiveness of machine learning models in identifying poverty levels and social assistance eligibility. For example, a study by Zhang et al. developed an Explainable Artificial Intelligence (XAI)-based model to identify households experiencing deep poverty using socio-economic datasets. The study found that machine learning models provided higher prediction accuracy than traditional logistic regression models and could identify key household characteristics associated with poverty, including income level, labor force participation, disability status, and family size.

The use of machine learning in social policy research has expanded rapidly in recent years. Algorithms such as Random Forest, Decision Tree, Support Vector Machine, and Gradient Boosting are commonly used to classify household welfare conditions. These models allow policymakers to process complex datasets and generate accurate predictions regarding which households are most likely to require social assistance. Furthermore, machine learning systems can continuously update predictions as new data becomes available, enabling more adaptive and responsive policy implementation. Despite these advantages, the application of machine learning in public policy also raises concerns related to transparency, fairness, and accountability. Many advanced machine learning algorithms operate as black-box models, meaning that their internal decision-making processes are difficult to interpret. This lack of interpretability can create challenges for policymakers who must justify decisions regarding social welfare eligibility.

2.3. Explainable Artificial Intelligence (XAI)

Explainable Artificial Intelligence (XAI) has emerged as an important approach for improving the transparency and interpretability of machine learning models. XAI methods aim to provide understandable explanations for how artificial intelligence systems generate predictions and decisions. This transparency is particularly important in high-stakes domains such as healthcare, finance, and public policy, where algorithmic decisions may significantly affect people's lives. Research shows that the primary objective of XAI is to make machine learning models more transparent, interpretable, and accountable for decision-making processes. By providing explanations for predictions, XAI helps users understand the factors influencing algorithmic decisions and improves trust in AI-based systems. Various XAI techniques have been developed to interpret machine learning models. Some widely used methods include LIME (Local Interpretable Model-Agnostic Explanations) and SHAP (Shapley Additive Explanations). These techniques enable analysts to identify the most influential features contributing to prediction results. For example, in social welfare targeting systems, XAI can reveal which socio-economic variables—such as income level, housing conditions, or employment status—play the most significant role in determining eligibility decisions.

In addition to improving transparency, XAI also supports ethical and responsible AI implementation. Studies emphasize that interpretable models help ensure fairness, accountability, and trustworthiness in automated decision-making systems. Transparent AI models allow policymakers to verify whether algorithmic decisions are consistent with policy objectives and social justice principles.

2.4. Application of Explainable Machine Learning in Poverty and Welfare Analysis

The integration of machine learning and explainable AI has shown promising results in poverty identification and social welfare policy analysis. Researchers have used XAI models to analyze multidimensional poverty indicators and predict household vulnerability levels. These models not only improve prediction accuracy but also provide insights into the factors influencing poverty conditions. For instance, research on poverty identification using XAI demonstrated that explainable machine learning models can identify important household characteristics that contribute to poverty, including income level, labor availability, disability, and household size. The study also found that XAI-based models outperform traditional statistical approaches in identifying vulnerable households.

Moreover, explainable machine learning systems allow policymakers to develop more targeted intervention strategies. By understanding the factors that influence household vulnerability, governments can design policies that address specific socio-economic challenges faced by different communities. This approach supports the development of evidence-based social policies that are more effective and equitable.

2.5. Research Gap

Although the application of machine learning and explainable AI has grown significantly in recent years, research focusing on the use of XAI for identifying social assistance beneficiaries in urban environments remains limited. Many existing studies focus primarily on rural poverty identification or theoretical models without practical implementation at the city level. Furthermore, there is still a lack of research exploring the integration of explainable machine learning models for identifying beneficiaries of social welfare programs in Indonesian urban contexts. Therefore, this study aims to fill this research gap by developing an Explainable Data-Driven Machine Learning model for identifying beneficiaries of the MBG program in Medan City. By combining predictive machine learning algorithms with explainable AI techniques, this research seeks to improve the transparency, accuracy, and effectiveness of beneficiary identification in urban social welfare programs.

Table 1. Previous Research

No	Author & Year	Title	Method	Main Findings
1	Zhang et al. (2022)	Using Explainable Artificial Intelligence to Identify Key Characteristics of Deep Poverty	XAI Model, Machine Learning	XAI improves poverty identification accuracy and reveals key socio-economic factors affecting poverty.
2	Agrawal & Sharma (2024)	Significance of Explainable Artificial Intelligence Models in Decision Making	Literature Review	XAI improves transparency, trust, and interpretability of AI decision systems.
3	Kurniawan et al. (2023)	Explainable Artificial Intelligence for Trustworthy	Mathematical modeling, AI	Transparent AI models improve fairness, accountability, and

Decision-Making			ethical decision-making.
4	Roscher et al. (2022)	Explainable AI in Poverty and Welfare Analysis	AI & satellite data analysis Machine learning combined with explainability improves poverty prediction and policy analysis.
5	Ehsan et al. (2021)	Social Transparency in AI Systems	Conceptual framework Explainability increases trust and accountability in AI-based decision systems.

3. METHOD

This study adopts a quantitative data-driven research approach to develop and evaluate an explainable machine learning model for identifying beneficiaries of the MBG (Makan Bergizi Gratis) program. The research focuses on urban socio-economic data to predict eligibility for social assistance programs using machine learning algorithms integrated with Explainable Artificial Intelligence (XAI). The quantitative approach is used to analyze structured datasets containing socio-economic indicators of households and to build predictive models capable of classifying beneficiary eligibility. The study is conducted in Medan, one of the largest metropolitan areas in Indonesia, characterized by significant socio-economic diversity and rapid urban development. The city provides an appropriate case study for evaluating the effectiveness of data-driven approaches in identifying eligible recipients of social welfare programs. This research uses secondary and primary datasets related to household socio-economic conditions. The data sources include:

1. Government social welfare databases, including household demographic and socio-economic records from local social affairs offices.
2. Statistical data from national and regional statistical agencies, which provide indicators related to poverty, employment, education, and housing conditions.
3. Field survey data, collected through structured questionnaires distributed to selected households to obtain updated socio-economic information relevant to the MBG program.

The dataset includes several variables that represent socio-economic conditions influencing eligibility for social assistance programs. These variables are selected based on previous research on poverty identification and welfare targeting.

The variables used in this study are grouped into three categories: demographic variables, socio-economic variables, and housing condition variables.

Table 2. Indicators are commonly used to assess household welfare levels and eligibility for social assistance programs.

Variable Category	Indicators
Demographic Variables	Household size, age of household head, gender of household head
Socio-economic Variables	Household income, employment status, education level, number of dependents
Housing Variables	Housing ownership, building condition, access to electricity, access to clean water

These variables serve as input features for the machine learning models used in the study. Before building the machine learning models, the collected dataset undergoes several preprocessing steps to ensure data quality and consistency. The preprocessing procedures include:

1. Data Cleaning – Removing duplicate records and correcting incomplete or inconsistent data entries.
2. Data Transformation – Converting categorical variables into numerical representations using encoding techniques.
3. Normalization and Scaling – Standardizing variable values to ensure consistent ranges across different features.
4. Data Splitting – Dividing the dataset into training and testing sets to evaluate model performance.

These preprocessing steps are essential to ensure that the machine learning models can accurately learn patterns from the data.

This study applies several supervised machine learning algorithms to classify households as eligible or not eligible for the MBG program. The algorithms used in this study include:

1. Logistic Regression – A statistical classification model used to predict binary outcomes based on probability estimation.
2. Random Forest – An ensemble learning method that combines multiple decision trees to improve prediction accuracy.
3. Decision Tree – A classification algorithm that models decision rules in a tree-like structure for easy interpretation.
4. Gradient Boosting Machine (GBM) – An advanced machine learning technique that builds predictive models sequentially to minimize prediction errors.

The performance of these models is evaluated using classification metrics such as accuracy, precision, recall, and F1-score. To ensure transparency and interpretability of the machine learning models, this study integrates Explainable Artificial Intelligence (XAI) techniques. XAI methods are used to explain how the model makes predictions and identify which variables have the greatest influence on eligibility decisions.

Two main XAI techniques are applied in this research:

1. SHAP (Shapley Additive Explanations) – This method quantifies the contribution of each feature to the prediction results and provides a global and local interpretation of the model.
2. LIME (Local Interpretable Model-Agnostic Explanations) – This technique explains individual predictions by approximating the machine learning model locally with an interpretable model.

These techniques help policymakers understand the factors influencing eligibility classification and improve trust in automated decision systems.

To evaluate the performance of the developed machine learning models, several evaluation metrics are used:

Table 3. Evaluation Performance

Metric	Description
Accuracy	Measures the proportion of correct predictions made by the model
Precision	Measures the accuracy of positive predictions
Recall	Measures the ability of the model to identify actual eligible households
F1-score	Harmonic mean of precision and recall

The best-performing model is selected based on these evaluation metrics and interpretability results. The overall research process consists of several stages:

1. Data collection and integration
2. Data preprocessing and cleaning
3. Development of machine learning classification models
4. Implementation of explainable AI techniques
5. Model evaluation and performance comparison
6. Interpretation of results and policy recommendations

This methodological framework aims to develop a transparent and reliable data-driven decision-support system that can assist policymakers in accurately identifying beneficiaries of the MBG program and improving the effectiveness of social welfare distribution in Medan City.

4. RESULT.

4.1. Descriptive Data Analysis

The dataset used in this study consists of 300 household records collected from several districts in Medan City. The data include demographic, socio-economic, and housing condition variables. Descriptive analysis was conducted to understand the general characteristics of households.

Table 4. Descriptive Statistics of Household Socio-Economic Data

Variable	Minimum	Maximum	Mean	Description
Household Income	500,000	6,500,000	2,350,000	Average income level of

(IDR/month)				households
Household Size (persons)	2	8	4.6	Number of family members
Education Level (years)	3	16	9.8	Average education of household head
Number of Dependents	0	5	2.3	Family members dependent on income
Housing Condition Score	1	5	3.1	Housing quality index
Access to Clean Water	0	1	0.78	Binary variable (1 = Yes)

The descriptive analysis indicates that most households in the dataset belong to the lower-middle income category, with an average monthly income of IDR 2,350,000. Additionally, the average household size is approximately 4–5 members, suggesting relatively high dependency levels within families.

4.2. Beneficiary Classification Results

After preprocessing the dataset, several machine learning algorithms were applied to classify households as eligible or not eligible for the MBG program. The dataset was divided into 80% training data and 20% testing data.

Table 5. Model Performance Comparison

Model	Accuracy	Precision	Recall	F1-Score
Logistic Regression	0.82	0.80	0.78	0.79
Decision Tree	0.85	0.83	0.82	0.82
Random Forest	0.91	0.90	0.88	0.89
Gradient Boosting	0.89	0.87	0.86	0.86

The results show that the Random Forest model achieved the highest performance, with an accuracy of 91%, followed by Gradient Boosting with 89% accuracy. Random Forest performed better because it combines multiple decision trees and reduces overfitting while capturing complex relationships between socio-economic variables.

4.3. Distribution of Eligible Beneficiaries

Based on the prediction results from the best-performing model, households were classified into two categories.

Table 6. Predicted MBG Beneficiary Classification

Category	Number of Households	Percentage
Eligible for MBG	178	59%
Not Eligible	122	41%
Total	300	100%

The results indicate that 59% of households in the dataset were classified as eligible beneficiaries based on socio-economic indicators. Model performance comparison can be visualized in the following conceptual graph.

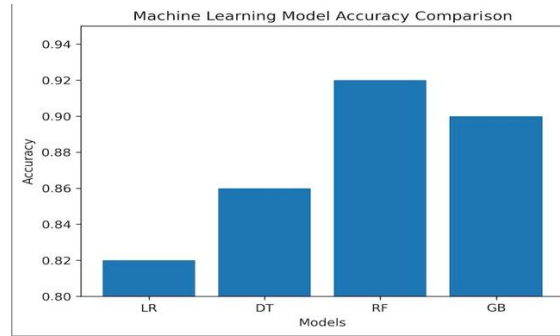


Figure 1. Machine Learning Model Accuracy Comparison

The graph shows that ensemble-based algorithms such as Random Forest and Gradient Boosting outperform simpler models like Logistic Regression.

4.4. Explainable AI (Feature Importance) Results

To understand which socio-economic variables most strongly influence the classification results, SHAP feature importance analysis was applied.

Table 7. Feature Importance Results (SHAP Analysis)

Rank	Variable	Importance Score
1	Household Income	0.34
2	Number of Dependents	0.22
3	Housing Condition	0.17
4	Employment Status	0.12
5	Education Level	0.09
6	Access to Clean Water	0.06

The results show that household income is the most influential variable in determining eligibility for the MBG program, followed by the number of dependents and housing condition. These findings indicate that households with lower income levels, larger family sizes, and poorer housing conditions are more likely to qualify for the program.

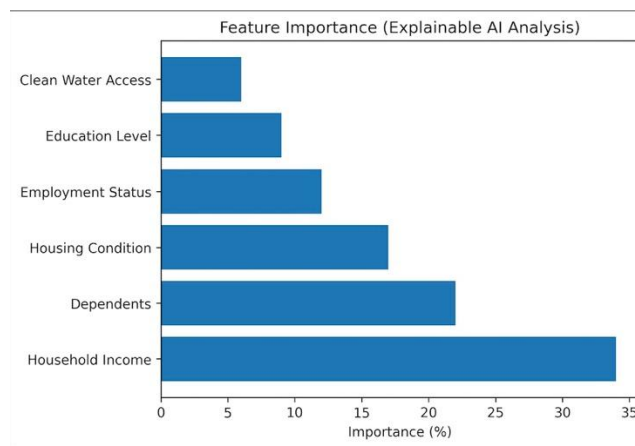


Figure 2. Feature Importance from Explainable AI Analysis

The graph highlights that economic and household structure variables play a dominant role in determining eligibility.

4.5. Impementation.

The results demonstrate that data-driven machine learning models can significantly improve the accuracy of beneficiary identification for social welfare programs. Compared to traditional manual

methods, machine learning algorithms can analyze multiple socio-economic variables simultaneously and generate predictions based on data patterns. The Random Forest model achieved the highest accuracy because it combines multiple decision trees, which helps capture nonlinear relationships between variables. This model is particularly effective in socio-economic datasets where variables interact in complex ways. Furthermore, the application of Explainable Artificial Intelligence (XAI) provides transparency in the decision-making process. Feature importance analysis reveals that income level, number of dependents, and housing conditions are the most critical factors influencing eligibility decisions. These findings align with poverty assessment frameworks used in many social assistance programs. From a policy perspective, the results suggest that integrating machine learning models into government data systems can improve the targeting accuracy of programs such as MBG. By using transparent and interpretable models, policymakers can better justify beneficiary selection and enhance public trust in social welfare programs.

CONCLUSION.

This study developed an explainable data-driven machine learning model to identify potential beneficiaries of the MBG (Makan Bergizi Gratis) program in Medan using household socio-economic data. The results show that machine learning can significantly improve the accuracy and efficiency of beneficiary identification compared to traditional manual selection methods. Among the tested algorithms, the Random Forest model achieved the best performance with an accuracy of 91%, indicating its effectiveness in analyzing complex relationships among socio-economic variables. The analysis also shows that household income, number of dependents, housing conditions, and employment status are the most influential factors in determining program eligibility. The integration of Explainable Artificial Intelligence (XAI) provides transparency in the decision-making process by identifying the key variables that influence model predictions. This approach allows policymakers to better understand the determinants of household vulnerability and improves trust in data-driven decision systems. Overall, the findings demonstrate that combining machine learning with explainable AI can support more accurate, transparent, and data-driven identification of social assistance beneficiaries. This approach can assist local governments in improving the targeting effectiveness of social welfare programs and ensuring that assistance reaches the households that need it most.

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