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Analysis and classification of capital assistance recipients at the Kediri trade and industry department using random forest

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Abstract
Capital assistance provided by the Kediri City Department of Trade and Industry often faces challenges related to the uncertainty of fund distribution, making it difficult to ensure the effectiveness of the assistance in improving business revenue. To address this, a prediction-based model is applied to evaluate the factors influencing the success of capital assistance in increasing recipients' income. This study aims to classify recipients based on business revenue outcomes using the Random Forest algorithm. Furthermore, the model identifies key factors affecting the success of assistance and offers recommendations for optimizing future distribution through feature importance analysis. The results demonstrate that the Random Forest model achieves an accuracy of 75%, highlighting its potential as a reliable tool for predicting the success of capital assistance. The feature importance analysis further reveals that training contributes 49% and business type 43%, emphasizing their crucial role in enhancing the effectiveness of future assistance programs.

1. Introduction

The COVID-19 pandemic has significantly disrupted the global economy, including Kediri City in East Java Province, Indonesia. Micro, small, and medium enterprises (MSMEs), the backbone of the local economy, faced severe operational and financial challenges. Studies indicate that the pandemic caused a sharp decline in MSME performance, with many businesses struggling to adapt to the new economic environment [1]. In response, the Kediri City Government launched the Business Capital Assistance Program through the Department of Trade and Industry [2]. This program, targeting MSMEs—particularly former cigarette factory workers and entrepreneurs in the trade sector—provided support to 11,993 individuals between 2021 and 2023 [3]. The program also records detailed recipient data, including business type, assistance amount, and monitoring and evaluation (monev) results, offering opportunities for further analysis [4].

Despite its broad implementation, the program still faces challenges, particularly in ensuring accurate targeting and effective utilization of funds. Previous research in East Java reported that many MSMEs experienced worsening performance during the pandemic due to inadequate support and limited adaptability to shifting market conditions [5]. Misallocation of capital assistance raises concerns about the program's effectiveness, especially in improving business revenue and long-term sustainability [4]. Other studies in Kediri highlight that combining capital assistance with structured support programs significantly boosts MSME performance [6]. Therefore, the main problem lies in how to ensure that capital assistance is distributed accurately and utilized effectively so that it produces meaningful economic outcomes. Addressing this issue requires analyzing recipient data to identify factors that influence successful fund utilization and revenue improvement [7].

To address these challenges, this study applies the Random Forest algorithm as a classification model for recipient data analysis. Classification techniques group data based on shared characteristics, uncovering patterns and trends in large datasets [8]. Random Forest is chosen due to its high accuracy, robustness in handling complex variable interactions, and consistent performance in classification tasks [9]. By identifying success factors, this approach provides insights into the drivers of MSME performance [10]. Furthermore, the evaluation of variable importance enables a deeper understanding of the factors contributing to business revenue growth [11]. Unlike previous studies that relied primarily on descriptive evaluations, this research offers a novel, data-driven perspective by leveraging machine learning to identify determinants of success among MSME recipients in Kediri. The specific objectives of this study are to: (1) identify the key factors that contribute to the effectiveness of capital assistance and (2) evaluate the accuracy of the Random Forest model in classifying successful versus unsuccessful recipients. The findings are expected to support the Department of Trade and Industry in designing more effective programs, ensuring better fund allocation, and ultimately strengthening MSME performance and local economic resilience.

2. Research Method

This study aims to identify the factors that influence the distribution of capital assistance, assess the effectiveness of targeted assistance distribution, and analyze and provide recommendations for more accurate targeting of capital assistance distribution in the future.

2.1 Algorithm Selection

Random Forest is a collection of decision trees that are built with randomly selected samples [12]. According to [13], the Random Forest algorithm can be used to classify large datasets. Random Forest is a technique for forming random forests that are used to classify or predict data [14]. This classification method is included in ensemble learning algorithms [15]. The advantages of Random Forest is its ability to handle dependencies and interactions between complex variables, as well as its ability to overcome overfitting [16]. This study utilizes the Random Forest classification algorithm to analyze and predict the success of capital assistance recipients. Random Forest was selected due to its ensemble nature, which reduces overfitting, handles both categorical and numerical features effectively, and provides insight into variable importance [17]. These strengths align well with the study's objective to produce interpretable and actionable recommendations for policymakers.

2.2 Research Instruments

Research activities require instruments to support the proper research design as tools to measure research variables [18]. In this study, the software used includes Google Colab and Microsoft Excel. The hardware used consists of a laptop with an Intel Core i3 processor and 8 GB of RAM.

2.3 Data Collection Method

The data used to find patterns or specific rules in this research were obtained from the dataset of capital assistance recipients to identify factors affecting business turnover and to analyze the data. The secondary data were provided by the Department of Trade and Industry of Kediri City in Excel (spreadsheet) format. Secondary data refers to data obtained from a third party, as the data used in this study was sourced from the relevant agency, the Department of Trade and Industry of Kediri City. The dataset spans from 2021 to 2023, with a total of 11,993 capital assistance recipients.

2.4 Research Method

In the initial stages of the research [19], the process began with: 1) data understanding, which focused on studying the structure, type, value, and benefits of the available data; 2) data preprocessing, which included handling missing values, removing unused columns, and normalizing the data; 3) Exploratory Data Analysis (EDA), where visualizations such as bar plots, pie charts, and box plots were created to examine the data's patterns and distributions; 4) data transformation, which was performed by converting categorical variables into numerical labels for easier analysis; 5) the feature selection step, which focused on selecting relevant features to enhance the model's effectiveness; 6) the modeling phase, where the Random Forest algorithm was applied to the data, utilizing the selected features to develop a predictive model; 7) evaluation, which was conducted to assess the model's performance using metrics such as accuracy, based on comparisons with other methods; and 8) the insights obtained from the application of the Random Forest model, which were used to support decision-making. Figure 1 illustrates the entire research process.

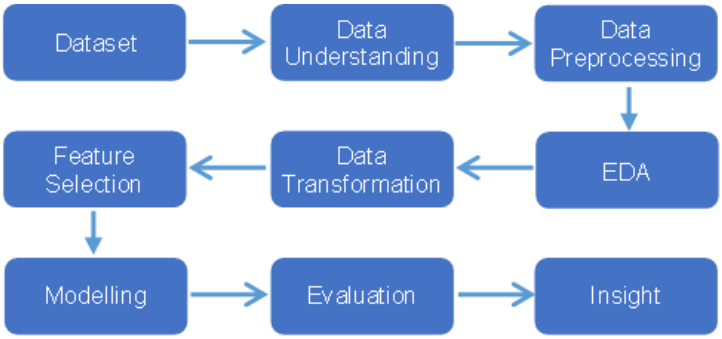

Figure 1. Research Methodology Flowchart

1) Dataset

This dataset is a collection of raw data that has not undergone any processing or preprocessing. The raw dataset was obtained from a third party, namely Kediri Trade and Industry Department. Below is Table 1, which presents the raw dataset. The following is the original dataset obtained from the Trade and Industry Department of Kediri.

Table 1. The Original Dataset

Name	Address	RT	RW	…	…	…	Gender	Age
ADE NURALINA	DHOHO D22	1	1	…	…	…	Female	57
HARI IRIYANTO	SEMAMPIR 1 NO 82B	1	1	…	…	…	Male	60
MARIDI	SEMAMPIR 1 86B	1	1	…	…	…	Male	57
MARYATIN	SEMAMPIR 1 NO 78B	1	1	…	…	…	Female	53
MURYONO	SEMAMPIR 1 NO 62	1	1	…	…	…	Male	62
LISAKURNIA AZIZADIYATI	SEMAMPIR 1 NO.90	1	1	…	…	…	Female	37
…	…	…	…	…	…	…	…	…

2) Data Understanding

This stage is the beginning of the data source that was analyzed. After the data were input, the next step was to examine and study the structure, type, content, and usage of the data to understand the initial dataset and the data to be used [20]. The output of this stage was a clear understanding of the data that would undergo the analysis process to support the next steps.

3) Data Preprocessing

The data preprocessing stage depended on the understanding of the data and the dataset generated from the previous steps [20]. The goal of this stage was to prepare the data in a format that is easy to process. This process also ensures the cleanliness and consistency of the data before it was used in training the algorithm model. Below is Table 2, which presents the results of the data preprocessing.

Table 2. Preprocessing Results

Year Received	Type of Business	Amount of Assistance	Type of infrastucture	Value of infrastucture	Monitoring and Evaluation Results	Training	Gender	Age
2023	trade business	2400000	gas cylinder	2120000	increased	marketing	female	57
…	…	…	…	…	…	…	…	…

4) EDA

The dataset that had undergone the pre-processing stage was then followed by the next step, which was data visualization, aimed at exploring and understanding the data from a visual perspective [21]. Exploratory Data Analysis (EDA) is a crucial step in investigating the data to uncover patterns within it [20].

5) Data Transformation

In the data transformation stage of the data analysis process, the goal was to convert raw data into a format that is more suitable or optimal for further analysis and modeling. This stage included the process of transforming data into a numerical format to make it more ready for analysis and modeling. Below is Table 3, which shows the results of the data transformation.

Table 3. Transformation Results

Year Received	Type of Business	Amount of Assistance	Type of Infrastucture	Value of Insfrastucture	Monitoring and Evaluation Results	Training	Gender	Age
2	331	2400000	5166	2120000	2	14	1	57
…	…	…	…	…	…	…	…	…

Table 3 shows the results of data transformation, where labeling was applied to the features. The *year received* feature assigns code 0 for 2021, code 1 for 2022, and code 2 for 2023. The *type of business* feature has codes ranging from 0 to 345 to represent actual data with high variation. The *infrastucture type* feature has codes ranging from 0 to 5860 to reflect diverse data variations. The *monitoring and evaluation result* feature is encoded as follows: code 0 for deceased, code 1 for withdrawn, code 2 for increased, code 3 for unchanged, code 4 for decreased, and code 5 for closed. The *training* feature has codes ranging from 0 to 30 to indicate actual data variations. The *gender* feature is encoded with code 0 for male and code 1 for female.

6) Feature Selection

This stage of the process involves feature selection, where the features to be used for data processing were chosen. The more relevant the selected data were, the easier the data processing would be. The selected features were defined along the x and y axes for the target feature or target variable.

7) Modeling

This process involved the method of development and selection of the algorithm to be used [22]. This study used the Random Forest Classifier model, which included several key stages in selecting and developing the model for building the predictive model. During this stage, the modeling process utilized several parameters, including *max_depth*, *max_features*, *n_estimators*, *min_samples_split*, *min_samples_leaf*, and *random_state* in the Random Forest Classifier model. According to [13], the formula to calculate the entropy value in the Random Forest model is presented in Equation 1.

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

Explanation:

- S : Target Variable
- i : Index
- n : Number of partitions of S
- p_i : The proportion of S_i relative to S

After calculating the entropy value, the next step was to calculate the gain value. According to [12], the formula for calculating gain is presented in Equation 2.

$$Gain(S, A) = Entropy\ (S) - \sum_{i=1}^{n} \frac{|s_i|}{|s|} * Entropy(s_i) \quad (2)$$

Explanation:

- s_i : The proportion of S_i relative to S

8) Evaluation

The evaluation process was an advanced stage to measure the performance of the classification system used in determining the accuracy level [23]. The evaluation was conducted to ensure that the modeling results aligned with the objectives of the study by comparing the evaluation results of the method used. The manual calculation to obtain the accuracy used Equation 3.

$$Accuracy\ = \frac{Number\ of\ correct\ predictions}{Total\ predictions} \quad (3)$$

9) Insight

The final stage, insight, involved drawing conclusions based on the findings from the previous stages. This stage aimed to summarize key results and provide valuable insights to support decision-making in the research process. By analyzing the effectiveness of financial aid distribution, identifying influential factors, and evaluating predictive modeling outcomes, this stage helped formulate recommendations for improving future aid distribution strategies.

3. Results and Discussion

3.1 Exploratory Data Analysis

The Exploratory Data Analysis (EDA) was carried out using descriptive statistics and visualization to understand the distribution of aid recipients. As shown in Figure 2 and Figure 3, most recipients received capital assistance between IDR 1–10 million, with a peak around IDR 2.65 million, while infrastructure support was dominated by values of IDR 2 million. This clustering suggests that fund allocation tends to follow uniform amounts, which may not fully reflect the diverse needs of MSMEs.

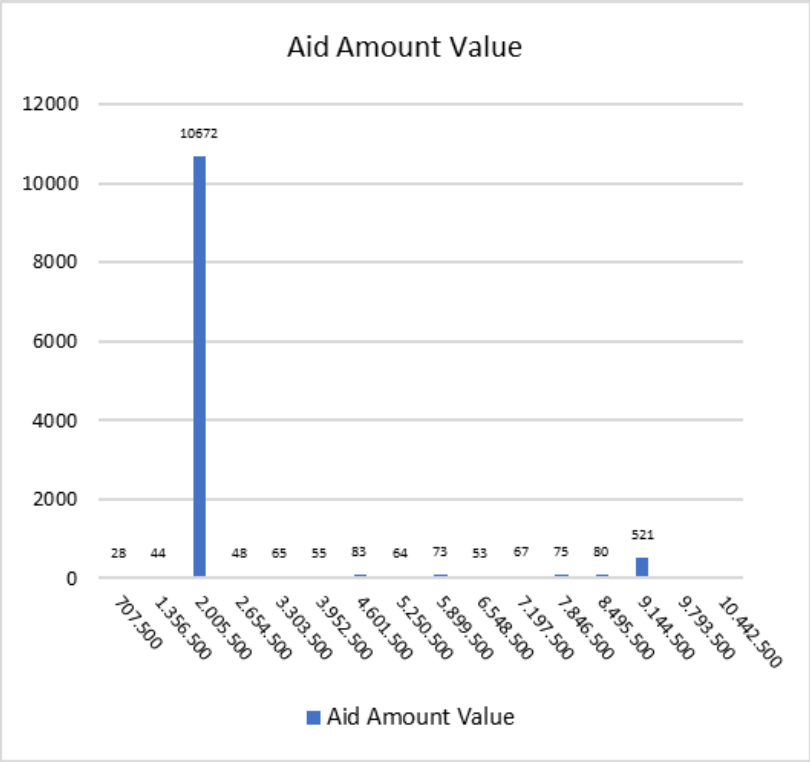

Figure 2. Results of EDA Feature Amount of Assistance

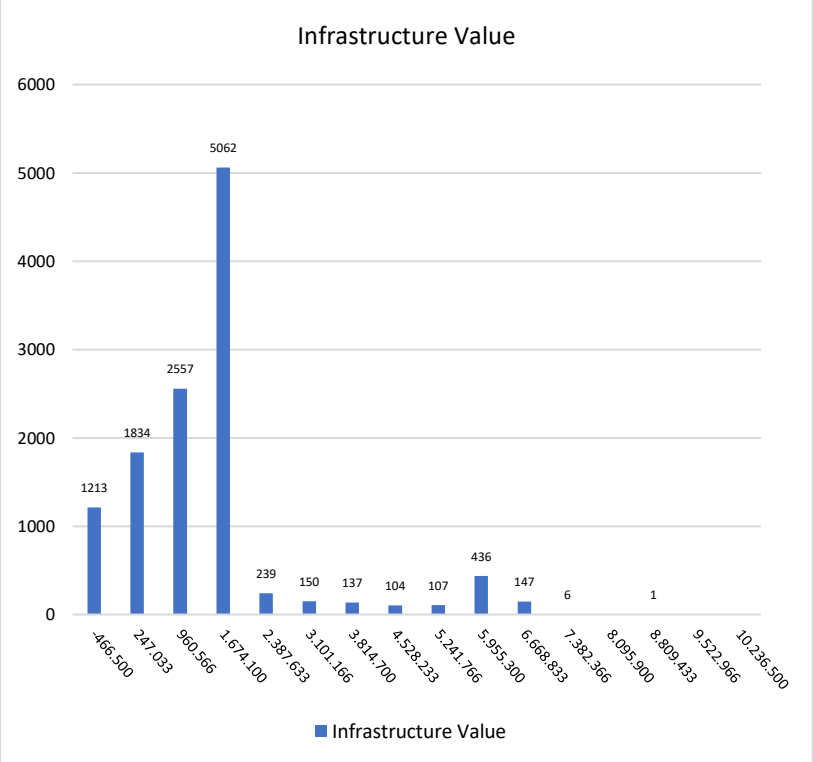

Figure 3. Results of EDA Feature Value of Infrastucture

The gender distribution in Figure 4 indicates that female recipients dominate (67.6%), possibly reflecting program targeting or greater responsiveness among women entrepreneurs. In terms of time trends, Figure 5 shows that the highest number of recipients was recorded in 2023 (88.6%), following the expansion of eligibility criteria from retired factory workers (2021) to the wider community (2022–2023).

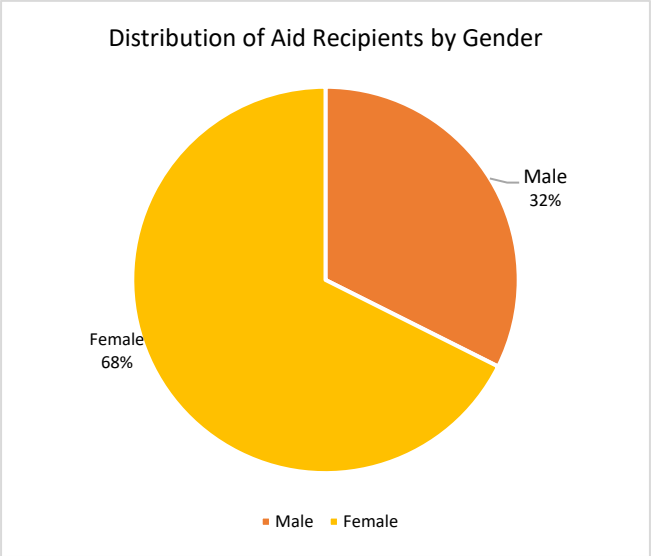

Figure 4. Results of EDA Feature Gender

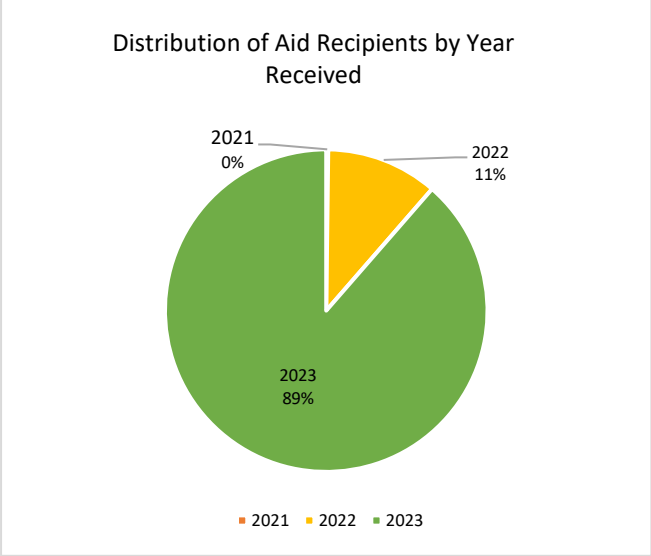

Figure 5. Results of EDA Feature Year Received

The analysis of business type in Figure 6 shows that the culinary sector is the most dominant, though with considerable variation. In contrast, handicrafts and creative industries display a more evenly distributed pattern. Age distribution in Figure 7 indicates that the majority of capital assistance recipients were in the 40-59 age group, totaling 6,342 recipients in 2023, 778 in 2022, and 0 in 2021. The second-largest group was 20-39 years old, consisting of 3,311 recipients in 2023 and 352 in 2022. Meanwhile, the 60-79 age group had 936 recipients in 2023 and 148 in 2022. The youngest group (0-19 years) recorded 30 recipients in 2023 and 12 in 2022, while the oldest group (80-99 years) had 10 recipients in 2023 and 6 in 2022. These findings suggest that most beneficiaries of capital assistance are in the productive age range (20-59 years), with the 40-59 group representing the dominant portion across all years observed.

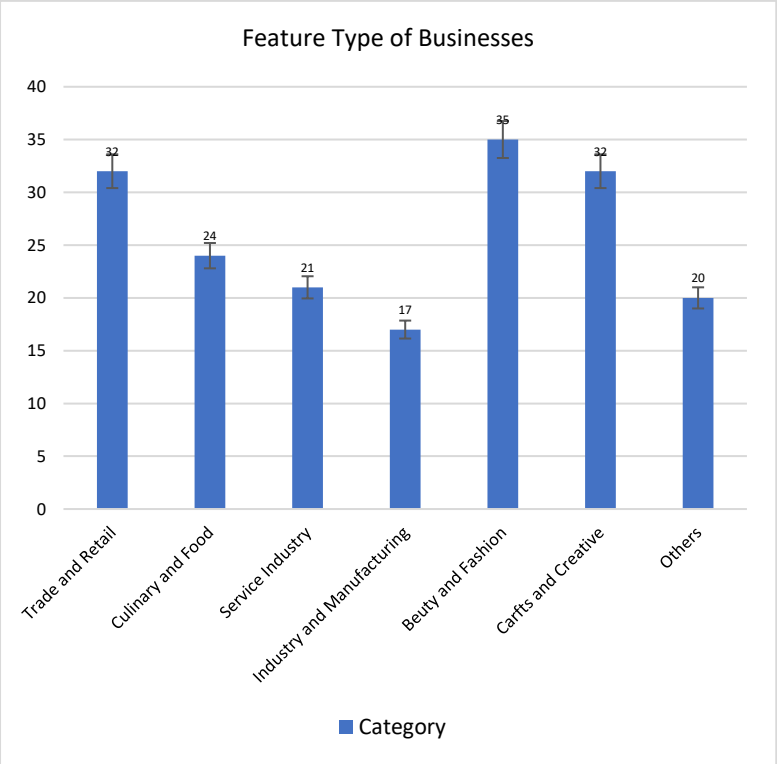

Figure 6. Results of EDA Feature Type of Businesses

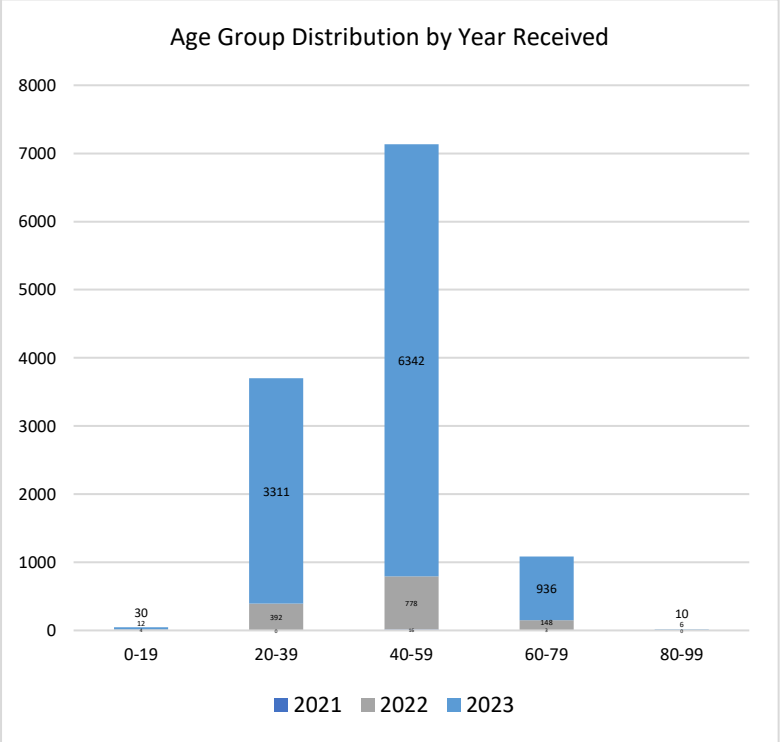

Figure 7. Results of EDA Feature Age and Year Achieved

Training also played an important role, as shown in Figure 8, with structured training programs strongly associated with improved outcomes. Revenue analysis in Figure 9 shows that in 2023, 9,644 recipients were classified as “Successful,” indicating a significant positive impact of program expansion, though sustainability over time requires further monitoring.

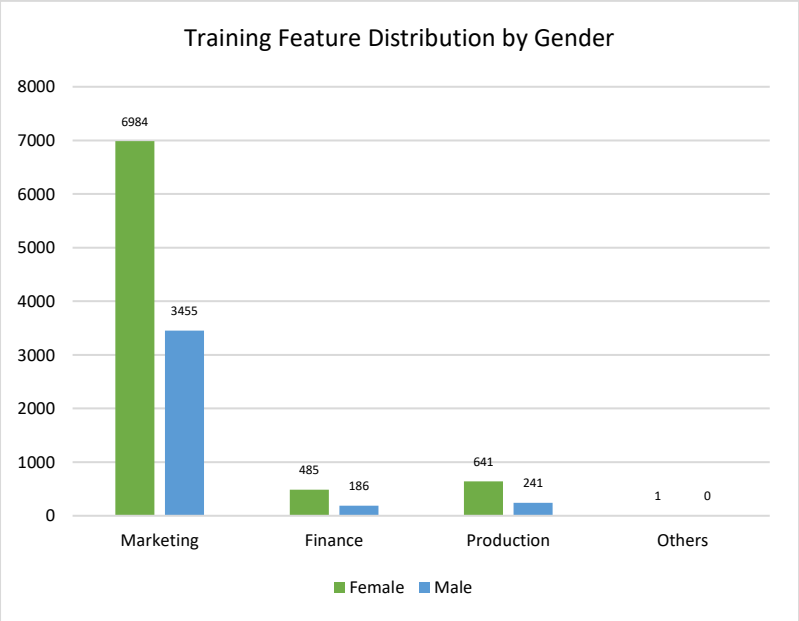

Figure 8. Training Feature EDA Result

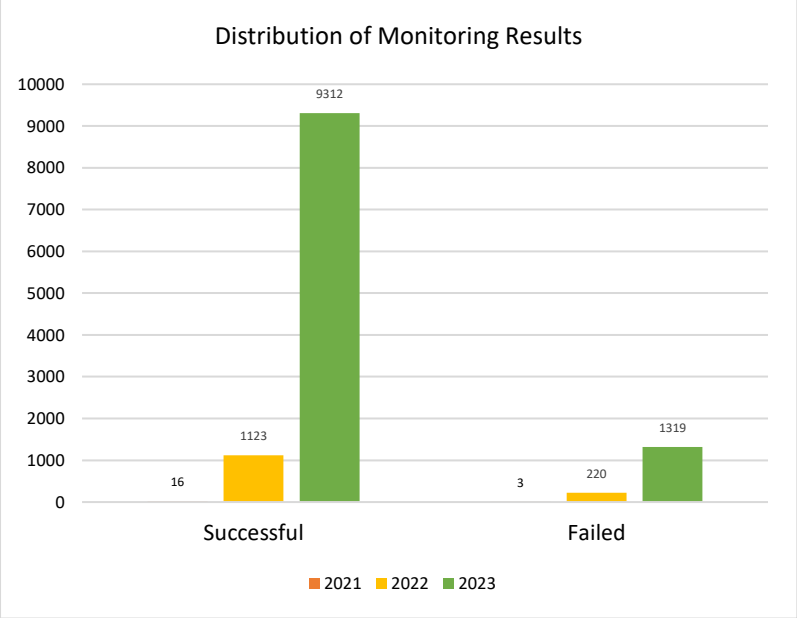

Figure 9. Results of Monev Features

3.2 Evaluation and Other Discoveries

The Random Forest model was applied to classify recipient outcomes and assess program effectiveness. The evaluation results in Table 4 show an overall accuracy of 75% and a training accuracy of 75.96%, indicating reliable classification performance without overfitting.

Table 4. Evaluation Results of the Method

Data	Capital Assistance Recipients
Methods	RF
Accuracy	75 %
Train Accuracy	75.96%
Top Feature Importance	Training
Bottom Feature Importance	Age

Feature importance analysis in Table 5 highlights training as the most influential factor (49%), followed by type of business (43.7%), while infrastructure value, equipment type, and age contribute minimally.

Table 5. Feature Importance

Feature	Importance
Training	0.499
Type of Business	0,437
Value of Infrastucture	0,016
Type of Equipment	0,014
Age	0.013

At the individual data point level in Table 6, marketing-related training was the strongest predictor (0.359), while specific age groups, such as 32 years, also showed moderate influence (0.142). These findings suggest that although age is generally less important, certain age brackets may influence outcomes in specific contexts.

Table 6. Feature Importance Discoveries for Data Points

Feature	Importance
Training _ marketing	0,359
Age_32	0,142
Type of Business _Food	0,093
Value of infrastucture _3.200.000	0.049
Type of Equipment _etalase	0,005

Compared with previous studies, the present research confirms the robustness of Random Forest in financial-related classification tasks. Research by Simarmata and Hartomo [21] achieved a recall of 97% in loan approval prediction, while Husen et al. [8] reported 100% accuracy in forest fire classification using Random Forest, outperforming K-Nearest Neighbors. Similarly, Arisusanto et al. [24] and Putra et al. [25], demonstrated the superior accuracy of Random Forest compared to other models. In addition, Rafael Agusto P. et al. [18] used feature importance to identify critical variables in a café business, which resonates with this study's finding that training is the most decisive factor for MSME success.

Overall, these results underline that Random Forest not only provides competitive accuracy but also offers interpretability through feature importance. This combination makes the model highly valuable for supporting policy design. The identification of training as the primary success factor implies that future capital assistance programs should integrate structured training modules alongside financial support to maximize long-term MSME resilience and growth.

4. Conclusion

Data exploration revealed patterns in the distribution and allocation of financial aid to MSME recipients in Kediri City. The Random Forest model successfully identified key factors influencing the success of capital assistance, with training emerging as the most important feature (49% importance). Within training, marketing-focused programs (35%) were particularly critical, especially for food sector businesses, which demonstrated higher potential to increase revenue (43%). Infrastructure support also contributed to improved business outcomes by enhancing product presentation. These findings provide actionable insights for policymakers: future capital assistance programs should prioritize targeted training, consider sector-specific interventions, and ensure adequate infrastructure support to maximize the effectiveness of fund distribution and enhance recipient business success.

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