An Ensemble Boosting Approach with Boruta Feature Selection for Predicting E-Payment Adoption

Mariana Purba[1*], Junaidi Junaidi[2], Lemi Iryani[3], Nia Umilizah[4], Handrie Noprisson[5], Nur Ani[6]
Faculty of Computer Science, Universitas Sjakhyakirti, Indonesia[1, 3, 4]
Faculty of Law, Universitas Sjakhyakirti, Indonesia[2]
Faculty of Informatics and Engineering, Universitas Dian Nusantara, Indonesia[5]
Faculty of Computer Science, Universitas Mercu Buana, Indonesia[6]

***Abstract*—This study examined the factors influencing the adoption of electronic payment systems among Micro, Small, and Medium Enterprises (MSMEs) and developed a predictive model to evaluate the suitability of e-payment implementation. The research applied an ensemble machine learning approach consisting of AdaBoost, Binomial Boosting, L2 Boosting, GLM Boosting, and Random Forest to predict the likelihood of e-payment adoption. The novelty of this study lay in optimizing ensemble learning performance through Boruta-based feature selection, which improved the identification of the most relevant predictors. Data were collected from 1,500 MSME owners in DKI Jakarta, Indonesia, using a structured questionnaire. The Boruta feature selection process was implemented using predictor variables as input features and the adoption decision as the target variable, with maxRuns = 50, pValue = 0.05, mcAdj = TRUE, and getImpRfZ as the feature importance function. The GLM Boosting model was implemented using a binomial family for binary classification with a learning rate of 0.1 and a stopping iteration of 50. The results indicated that Perceived Risk, Perceived Usefulness, Subjective Norms, and Loyalty to E-payment Brands were the most influential factors affecting adoption. Among all models, GLM Boosting achieved the best performance with the highest test accuracy of 82.30%, demonstrating strong predictive capability and generalization performance. These findings provided practical insights for MSME owners and policymakers in designing strategies to improve e-payment adoption and supported the development of more effective digital financial inclusion policies.**

***Keywords*—E-payment; AdaBoost; binomial boosting; L2 boosting; GLM boosting; Boruta procedure**

I. Introduction

The rapid advancement of information technology in recent years has supported changes across various industrial sectors, including the financial sector [1], [2], [3]. One of the most significant innovations in finance has been electronic payment (e-payment), which utilized technology to facilitate digital financial transactions without the need for cash or physical cards [4]. E-payment supported various types of transactions, such as payments through mobile applications, quick response (QR) codes, and other digital payment methods [5]. The development of electronic payment systems or e-payment provided ease of transactions, benefiting both consumers and business owners [6].

In Indonesia, micro, small, and medium enterprises (MSMEs) have been a key driver of the country's economy [7]. According to data Indonesian government, MSMEs contributed more than 60% to Gross Domestic Product (GDP) of Indonesia and absorbed over 97% of the workforce [8]. The role of MSMEs in the Indonesian economy was crucial, yet many MSME owners faced difficulties in adopting changes, particularly in the area of electronic payments [9]. Despite its potential to accelerate transactions and provide an alternative to manual or cash-based systems, MSMEs were still hesitant to embrace electronic payments due to several challenges, such as limited infrastructure, low digital literacy, and reliance on cash transactions [10].

The use of digital payment systems provided an alternative payment method to support operational efficiency, reduce the risk of fraud, simplify transaction recording, and expand market reach by offering a more modern payment approach [11]. However, in its implementation, the adoption of e-payment by MSMEs posed several risks. Issues such as implementation costs, trust in technology, and social influences existed if there was no analysis of the adoption of this technology among MSMEs, which were the target users of e-payment systems [12].

According to previous research, the adoption of e-payment needed to be analysed based on both external and internal factors derived from the user environment. Therefore, to gain a deeper understanding of the factors influencing MSME decisions of owners to adopt e-payment, an approach capable of accurately analysing various variables was required [13]. One such approach that could be used was machine learning with ensemble methods. This technique could be employed to identify patterns within the data and predict e-payment adoption behaviour, providing policy recommendations for the government and strategic insights for MSMEs [14].

Previous studies have employed ensemble-based machine learning techniques, such as Random Forest, to predict technology adoption across various fields. Research by Natarajan et al. (2024) predicted the adoption of AI technology in the telecommunications industry using the Random Forest algorithm. This study aimed to understand how users in the telecom sector embraced AI technology, utilizing machine learning methods to predict adoption rates based on relevant variables within the industry [15].

Mallinger et al. (2024) conducted an analysis of technology adoption in the context of smart farming, employing Random Forest to examine the factors influencing the adoption of technology in smart agriculture. The analysis translated these

*Corresponding author.

findings into technological requirements, business strategies, and policy interventions that could support the implementation of this technology in the agricultural sector [16]. Research by Carbo-Valverde et al. (2020) analyzed technology adoption using a Random Forest approach among bank customers to understand user behavior when adopting new technologies in banking. This research sought to identify the key factors that influenced customers decisions to adopt new technological services in the banking industry [17].

Choi et al. (2024) examined technology adoption in wearable IoT devices using machine learning algorithms. This study identified 17 major predictors influencing adoption, with data collected from women in their teens and twenties, who were found to be the most likely core consumers of wearable devices [18]. Jain et al. (2024) explored the adoption of mobile health applications through a machine learning approach, utilizing Random Forest. The study assessed 12 metrics based on perceived usefulness and 8 based on perceived ease of use. Data was gathered from 200 respondents, of which 102 were mobile health application users [19].

Based on previous research, this study aimed to analyse the factors influencing the adoption of e-payment in MSMEs and to develop a predictive model that could assist in mapping the suitability of e-payment implementation based on the characteristics and attitudes of business owners or consumers. The predictive model was developed using an ensemble machine learning approach, i.e. AdaBoost, Binomial Boosting, L2 Boosting, GLM Boosting, and Random Forest, all of which are known for their ability to handle complex classification and prediction problems.

As the novelty, this research also optimized the ensemble method by performing feature selection using the Boruta procedure, aimed at selecting the most relevant features for predicting the suitability of e-payment implementation. Feature selection is a critical step in machine learning that involves identifying and retaining the most relevant variables or features from a dataset to improve model performance, reduce overfitting, and enhance computational efficiency [20], [21].

The Boruta procedure is a feature selection method designed to identify all relevant, interesting features in a dataset [22], [23]. Unlike traditional methods that focus on removing irrelevant or redundant features, Boruta aimed to retain all the features that are potentially important for the prediction task [24], [25]. The procedure works by comparing the importance of each feature in the dataset to a random feature that has no relation to the outcome [22], [26].

II. Research Methodology

The methodology of this research involved several key stages, starting with data collection, where relevant data from MSMEs were gathered, including business characteristics and consumer attitudes towards e-payment adoption. Dataset preparation followed, involving cleaning and preprocessing the data to ensure its quality and suitability for analysis. Feature selection was then performed using the Boruta procedure to identify the most influential factors affecting e-payment adoption, enhancing model accuracy. In the prediction modelling phase, several machine learning algorithms were applied, including AdaBoost, Binomial Boosting, L2 Boosting, GLM Boosting, and Random Forest, to create robust predictive models. Finally, recommendations were provided based on the model findings, offering insights into the key factors that influence the successful implementation of e-payment in MSMEs. The research methodology can be seen in Fig. 1.

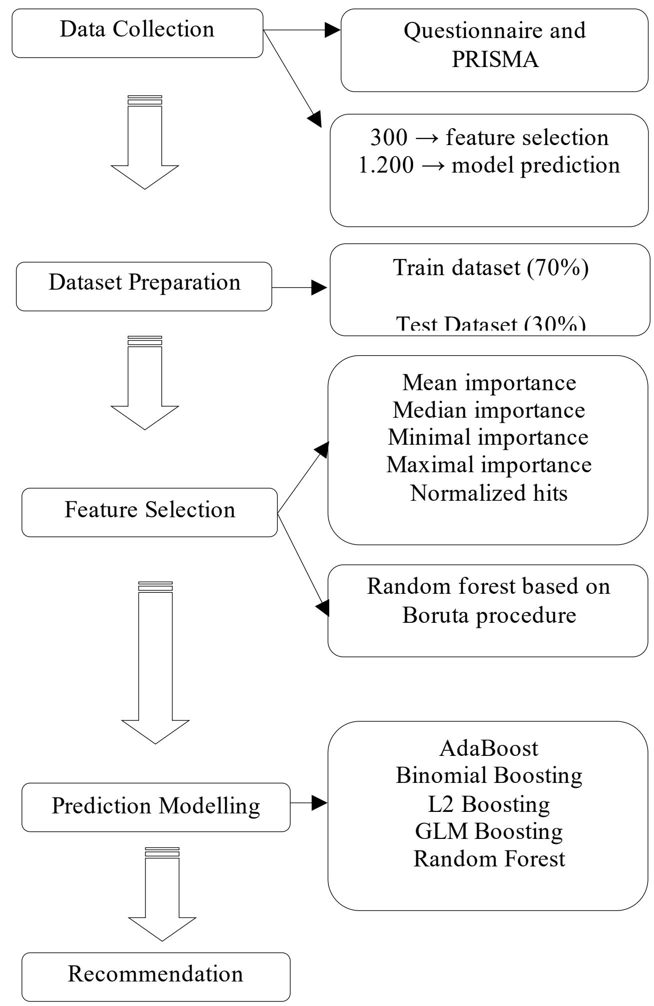

Fig. 1. Research methodology.

This research aimed to analyse the factors influencing the adoption of e-payment in Micro, Small, and Medium Enterprises (MSMEs) and to develop a predictive model for the implementation of e-payment in MSMEs based on the characteristics and attitudes of the business owners or consumers. The prediction used an ensemble machine learning approach with a binary prediction label, namely suitable for implementation with label (1) and not suitable for implementation with label (0).

Data was collected using a questionnaire distributed to 1,500 MSME owners in Jakarta, Indonesia. The e-payment questionnaire consisted of items adapted from previous literature based on the PRISMA method. Each variable measured in this study was evaluated using more than three items for each latent variable. These items were assessed using a five-point Likert scale (1 = strongly disagree, 5 = strongly agree).

Based on the PRISMA results, the key variables measured in the questionnaire included perceived usefulness (PU), which MSME owners felt that e-payment could enhance the efficiency and effectiveness of their business. The second variable is perceived ease of use (PE), where MSME owners or consumers felt that e-payment was easy to use. Other variables measured included perceived risk (PR), as outlined by [27], [28], and perceived trust (PT), as described by [28]. Additionally, personal innovativeness in information technology (PI), based on the work of [4], [29]. Perceived enjoyment (PE), according to [30], was also measured, alongside loyalty to the e-payment brand (LB), based on [31]. Lastly, perceived quality (PQ) was evaluated, following the research of [6].

After data collection, the first step was to clean the data by addressing missing values and outliers. Any incomplete or invalid data were removed from the analysis. Some independent variables were transformed into suitable formats for model analysis, such as encoding categorical variables into numerical ones. Feature selection was then performed using Random Forest based on the Boruta procedure, with feature importance evaluated through mean, median, minimal, maximal, and norm hit importance measures.

The Boruta model was implemented using predictor variables as input features (x) and the target variable as the response variable (y). The maximum number of iterations was set using *maxRuns* = 50 to allow sufficient repetitions for stable feature evaluation. The significance level was defined with pValue = 0.05, while multiple comparison adjustment was enabled using *mcAdj* = TRUE to reduce the risk of false-positive feature selection. Feature importance was calculated using the default Random Forest importance function (*getImpRfZ*), which is based on Z-score importance values derived from Random Forest. Additionally, *doTrace* = 2 was used to provide detailed iteration output during the selection process.

The processed data was used to build a predictive model using ensemble machine learning. This approach involved several machine learning algorithms to enhance prediction accuracy. The ensemble algorithms i.e. AdaBoost, Binomial Boosting, L2 Boosting, GLM Boosting dan Random Forest.

In this experiment, the model, which had been trained using AdaBoost, Binomial Boosting, L2 Boosting, GLM Boosting, and Random Forest, determined the coefficient values for each feature. Suppose we already have coefficients based on the feature selection results, for example, $\beta_0 = -1.2, \beta_1 = 0.5, \beta_2 = 0.3$ for new data are $X_1 = 2, X_2 = 3$, the linear predictor value can then be calculated based on the coefficients and the input features using the Eq. (1)

$$f(x) = \beta_0 + \beta_1 X_1 + \beta_2 X_2 \quad (1)$$

Using the formula above, the value of $f(x)$ can be calculated by substituting the values of X and β obtained previously. In the experimental process, the function used in the algorithm or model is the sigmoid function, which is calculated using the Eq. (2).

$$P(Y = 1 \mid X) = \frac{1}{1 + \exp(-f(x))} \quad (2)$$

To calculate the value of P, the previously computed $f(x)$ can be used. After calculating the probability, predictions can be made with a binary classification, indicating whether the e-payment adoption is suitable (class 1) or not suitable (class 0). In this study, the binary classification threshold is set at 0.5. If the probability $P(Y = 1 \mid X) \geq 0.5$,, the prediction will be class 1; otherwise, if the probability $P(Y = 1 \mid X) < 0.5$, the prediction will be class 0.

The developed model was evaluated using binary prediction evaluation metrics, such as accuracy, precision, recall, and F1-score. The model produced binary prediction labels for each MSME, classifying them as "suitable for implementation" (1) or "not suitable for implementation" (0) regarding e-payment adoption. After the predictive model was applied, the results were analysed to identify the key factors influencing decisions to adopt e-payment. Based on these insights, recommendations were provided to the government to accelerate e-payment adoption, as well as to policymakers for designing policies that support the adoption of digital payment technologies in the MSME sector.

III. Result and Discussion

The aim of this research was to analyse the factors that influenced the adoption of electronic payment (e-payment) systems in Micro, Small, and Medium Enterprises (MSMEs) and to develop a predictive model that could assess the suitability of implementing e-payment based on the characteristics and attitudes of business owners or consumers. By utilizing ensemble machine learning techniques, including AdaBoost, Binomial Boosting, L2 Boosting, GLM Boosting, and Random Forest, the study sought to predict the likelihood of e-payment adoption. Additionally, the research aimed to optimize the model's performance through feature selection using the Boruta procedure, which identified the most relevant features for accurately predicting e-payment adoption.

In this study, feature selection was conducted using the Random Forest algorithm in conjunction with the Boruta procedure, which assessed feature importance based on several metrics, including mean, median, minimal, maximal, and norm hit importance. This process helped identify the most relevant features for predicting e-payment adoption with the result can be seen in Table I.

The Boruta feature selection results showed that most variables were classified as confirmed features, indicating their strong contribution to predicting e-payment adoption among MSMEs. Variables related to perceived usefulness (PU), subjective norms (SN), perceived trust (PT), perceived risk (PR), and loyalty to e-payment brands (LB) generally demonstrated high importance values and were retained for further modeling. In particular, PU1–PU4 achieved the highest importance scores with norm values close to 1.00, indicating that perceived usefulness was one of the strongest predictors in the model. Several variables such as PE3, PT5, and PQ1 were rejected because they showed very low or negative importance values, suggesting minimal influence on adoption decisions. Some variables, including PE1, LB3, PQ2, and PQ5, were categorized as tentative, indicating moderate relevance that required further consideration.

TABLE I. RESULT OF FEATURE SELECTION

Item	Mean	Med	Min	Max	Norm	Rs
PE1	6.17	6.31	3.53	8.41	0.89	*
PE2	3.89	3.94	1.43	6.37	0.79	*
PE3	−1.11	−1.13	−1.99	1.21	0.00	×
PE4	4.19	4.22	2.29	6.22	0.87	*
PE5	3.91	4.01	1.12	6.21	0.78	*
PR1	5.02	5.11	2.59	6.691	0.89	*
PR2	4.48	4.61	1.79	6.71	0.88	*
PR3	3.57	3.52	−0.03	5.41	0.71	*
PR4	5.11	5.02	2.42	6.72	0.89	*
PU1	12.97	12.95	12.12	14.89	0.98	*
PU2	15.97	15.80	14.95	17.81	0.99	*
PU3	13.49	13.13	11.12	14.35	0.99	*
PU4	15.90	17.04	14.45	17.71	0.99	*
PT1	4.82	4.52	3.63	5.29	0.85	*
PT2	4.68	4.71	−0.01	6.56	0.72	*
PT3	5.25	5.31	3.16	5.96	0.85	*
PT4	5.64	5.72	2.15	7.52	0.92	*
PT5	−2.17	−2.14	−2.05	2.11	0.00	×
PT1	9.96	10.17	8.73	11.39	0.98	*
PT2	9.90	9.98	7.91	11.31	0.98	*
PT3	8.05	7.42	4.85	9.32	0.97	*
PT4	7.10	7.12	5.38	8.37	0.97	*
SN1	8.62	8.42	7.47	11.52	0.96	*
SN2	9.42	9.51	8.18	11.31	0.95	*
SN3	10.12	10.21	9.21	12.34	0.93	*
SN4	11.22	11.51	12.32	11.21	0.90	*
PE1	2.52	2.52	0.97	5.21	0.51	~
PE2	4.15	5.72	3.27	5.98	0.87	*
PE3	5.71	5.22	0.80	7.16	0.82	*
LB1	6.11	6.17	4.21	4.99	0.89	*
LB2	3.72	−0.05	4.12	5.24	0.72	*
LB3	2.81	2.85	1.07	4.90	0.56	~
LB4	4.12	1.12	4.41	6.14	0.74	*
PQ1	−1.25	−1.51	−1.97	2.24	0.00	×
PQ2	1.07	1.31	1.08	3.90	0.46	~
PQ3	4.21	−0.28	3.28	6.12	0.75	*
PQ4	8.17	8.21	6.89	11.31	0.96	*
PQ5	1.72	2.13	1.06	4.31	0.49	~
PQ6	10.38	10.37	11.41	12.17	0.90	*
PQ7	11.21	11.82	11.32	11.31	0.91	*

*=confirmed, ~=tentative, ×=rejected, Rs= result

Based on feature selection process, normalized hits importance was used to assess the consistency and impact of certain factors in influencing MSMEs decisions to adopt digital payment technologies. The normalized hits measured particular factor was considered important during the feature selection process, with values normalized between 0 and 1. This study attempted to calculate the value of normalized hits average to show the importance of the variable of MSMEs decisions to adopt digital payment. The normalized hits average can be seen in Fig. 2.

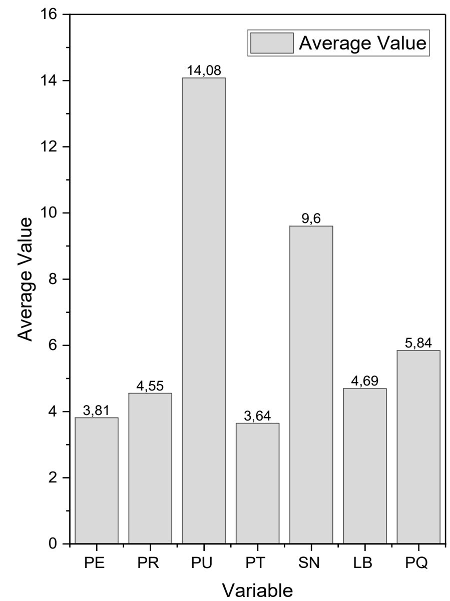

Fig. 2. Value of normalized hits.

Factors that were often deemed important in influencing e-payment adoption decisions had high normalized hits values, indicating that these factors were stable and relevant in the decision-making process. Conversely, factors with low normalized hits values were often irrelevant and less influential compared to other factors. A normalized hits value between 0.8 and 1.0 indicated factors that had a strong influence on the adoption decision, while values between 0.5 and 0.8 indicated factors that were moderately influential but not consistent, and values below 0.5 suggested factors that were less relevant or weak, thus contributing insignificantly to the adoption decision.

The perceived enjoyment (PE) variable had an average value of 3.81, indicating that the enjoyment experienced by MSME owners or consumers when using e-payment had a moderate influence, but was not the most crucial factor in the adoption process. The perceived risk (PR) variable had a normalized hits average of 4.55, suggesting that the perception of risk associated with using e-payment played a significant role in hindering adoption.

The perceived usefulness (PU) variable scored an average of 14.08, reflecting the belief among MSME owners that e-payment could enhance the efficiency and effectiveness of their businesses. The perceived trust (PT) variable, with an average of 3.64, showed that trust in the e-payment system was an influential factor, with lower levels of trust potentially hindering adoption, although it was not the most dominant factor. The subjective norms (SN) variable received an average of 9.60.

The loyalty to the e-payment brand (LB) variable had an average value of 4.69, showing that loyalty to a payment brand influenced MSME willingness of owners to adopt the e-payment system provided by trusted financial institutions. Finally, the perceived quality (PQ) variable, with a normalized hits value of 5.84, indicated that the quality of the e-payment system, such as reliability and ease of use, was an important factor, though less crucial compared to Perceived Usefulness or Subjective Norms.

After completed feature selection, a total of 1,200 data points based on feature selection were used for building the prediction model, with 70% of the data as many 840 data allocated for training the model and the remaining 30% as many 360 data used as the test dataset. In this experiment ensembled machine learning algorithms, including AdaBoost, Binomial Boosting, L2 Boosting, GLM Boosting, and Random Forest, were employed to train the model on the training dataset. The performance of each model was then evaluated using the test dataset, allowing for a comparison of their accuracy in predicting the adoption of e-payment by MSMEs as depicted in Table II.

TABLE II. ACCURACY OF RESEARCH EXPERIMENT

Algorithm	Train (70%)	Test (30%)
AdaBoost	86.25%	78.21%
Binomial Boosting	85.12%	78.56%
L2 Boosting	89.20%	80.17%
GLM Boosting	90.10%	82.30%
Random Forest	85.50%	79.21%

In the experiment, the AdaBoost algorithm achieved an accuracy of 86.25% on the training dataset and 78.21% on the test dataset. These results indicate that the model performed well on the training data, demonstrating its ability to learn the patterns in the data. The complete process of AdaBoost experiment for every epoch can be seen in Fig. 3.

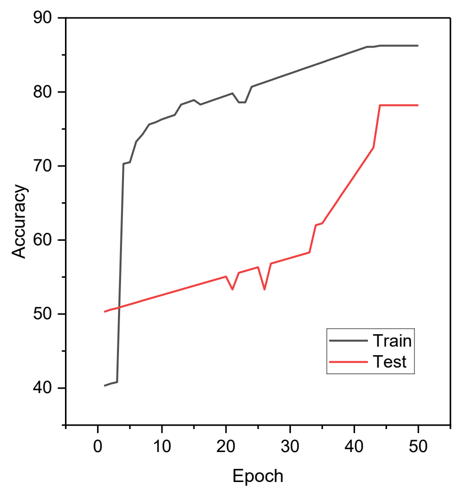

Fig. 3. Accuracy of AdaBoost per epoch.

The Binomial Boosting algorithm achieved an accuracy of 85.12% on the training dataset and 78.56% on the test dataset. Binomial Boosting is a variant of boosting techniques that focuses on binary classification tasks, making it particularly suited for problems like predicting e-payment adoption (which typically involves a binary outcome). The relatively high training accuracy indicates that the model is effectively capturing the relationship between the input features and the target variable. However, similar to AdaBoost, the gap between the training and test accuracy suggests that the model might be overfitting. The complete process of Binomial Boosting experiment for every epoch can be seen in Fig. 4.

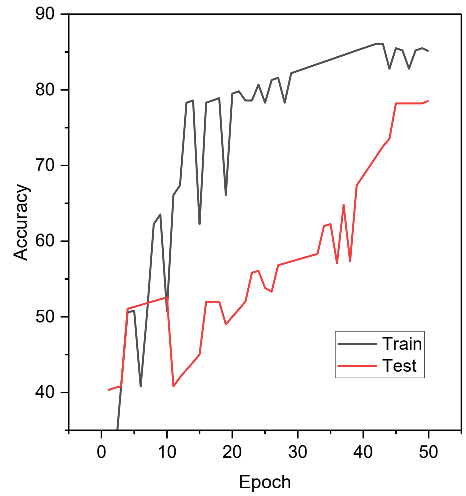

Fig. 4. Accuracy of binomial boosting per epoch.

The L2 Boosting algorithm showed an accuracy of 89.20% on the training dataset and 80.17% on the test dataset. L2 Boosting is an advanced boosting technique that focuses on minimizing the squared error between the predicted and actual values. This algorithm demonstrated the highest training accuracy among all the models, suggesting that it is able to capture the patterns in the data more effectively. Additionally, its relatively strong performance on the test dataset indicates that it generalizes well, with less overfitting compared to AdaBoost and Binomial Boosting. The results suggest that L2 Boosting is a powerful algorithm can be seen in Fig. 5.

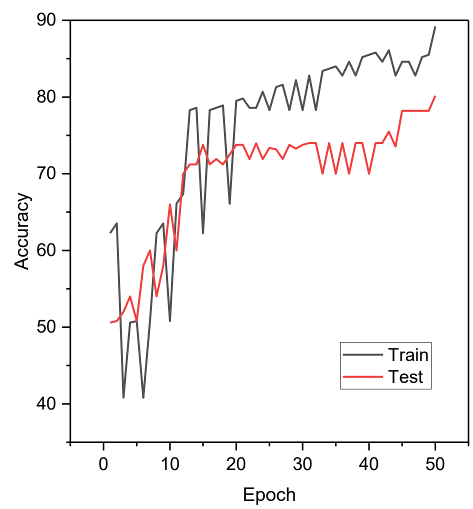

Fig. 5. Accuracy of L2 boosting per epoch.

The accuracy L2 Boosting increased significantly during the early epochs, indicating that the model quickly learned important patterns from the dataset. As the number of epochs increased, the training accuracy continued to improve and eventually reached approximately 89.20%, while the testing accuracy gradually increased and stabilized around 80.17%. Although minor fluctuations were observed in the testing curve, the overall trend indicated consistent improvement in model performance.

The GLM Boosting algorithm achieved an accuracy of 90.10% on the training dataset and 82.30% on the test dataset, the highest test accuracy among all the models. Generalized Linear Model (GLM) Boosting is an approach that applies boosting techniques to a linear model, improving its predictive accuracy by combining weak learners. The results show that GLM Boosting performs exceptionally well, both in training and on unseen test data. The higher test accuracy indicates that the model has a strong ability to generalize, likely due to its ability to fit both linear and non-linear relationships in the data. The complete process of GLM Boosting experiment for every epoch can be seen in Fig. 6.

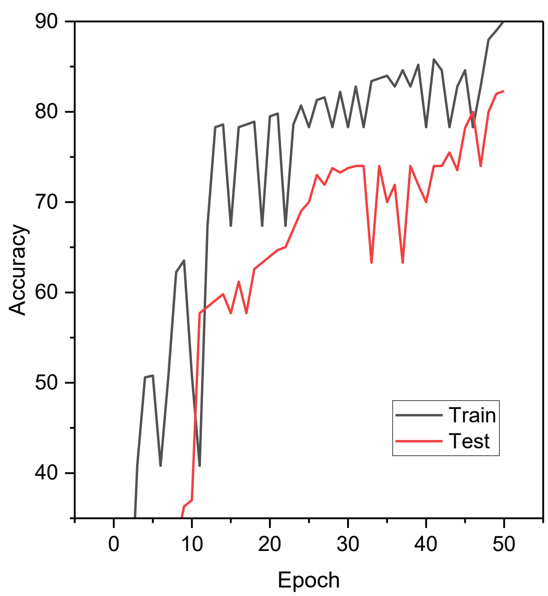

Fig. 6. Accuracy of GLM Boosting per epoch.

The Random Forest algorithm achieved an accuracy of 85.50% on the training dataset and 79.21% on the test dataset. Random Forest is an ensemble method that combines multiple decision trees to create a more stable and accurate prediction model. It is known for its ability to handle large datasets with high dimensionality and is less prone to overfitting compared to other models like AdaBoost. However, in this experiment, the performance gap between the training and test accuracies suggests that there might still be some overfitting. Despite this, Random Forest consistently performs well on both training and test data, indicating that it is a solid model for e-payment adoption prediction. The complete process of Random Forest experiment for every epoch can be seen in Fig. 7.

The training accuracy (black line) increased rapidly in the early epochs and then gradually stabilized, eventually reaching approximately 85.50%. Meanwhile, the testing accuracy (red line) showed several fluctuations in the early stages but generally followed an upward trend as the epochs increased. Toward the final epochs, the testing accuracy improved and reached around 79.21%. This pattern indicated that the Random Forest model progressively learned the underlying patterns in the dataset, while the relatively small gap between training and testing accuracy suggested that the model maintained a reasonable generalization performance without severe overfitting.

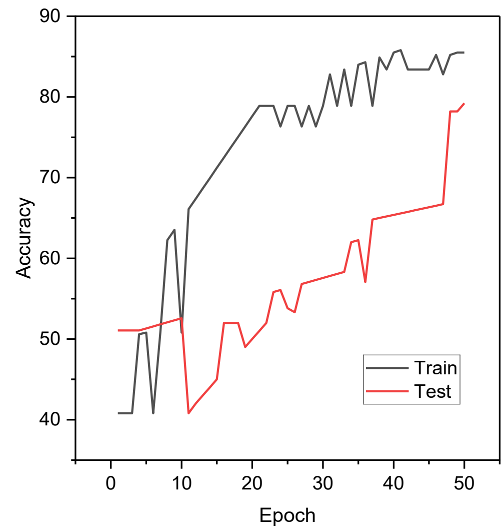

Fig. 7. Accuracy of random forest per epoch.

The results demonstrated high predictive accuracy, with the GLM Boosting model achieving the best overall performance. The GLM Boosting model was implemented using a binomial family for binary classification, with a learning rate (*nu*) of 0.1 and a stopping iteration (*mstop*) of 50, which were commonly used default settings to ensure stable learning and balanced model complexity. Predictor variables were centred (centre = TRUE) to improve model stability and reduce potential bias caused by differences in variable scales. This ensemble boosting approach combined with Boruta feature selection provided an effective framework for predicting e-payment adoption.

IV. Conclusion

This study successfully identified key factors influencing the adoption of e-payment systems in Micro, Small, and Medium Enterprises (MSMEs) in Indonesia, and developed a predictive model to assess the suitability of e-payment implementation based on the characteristics and attitudes of business owners or consumers. The analysis showed that factors such as Perceived Risk, Perceived Usefulness, Trust, Subjective Norms, Loyalty to the E-payment Brand, and Perceived Quality played significant roles in the adoption process. The study demonstrated the effectiveness of ensemble machine learning methods, i.e. AdaBoost, Binomial Boosting, L2 Boosting, GLM Boosting, and Random Forest in predicting e-payment adoption. The feature selection process, optimized through the Boruta procedure, significantly improved the prediction model by selecting the most relevant features. The results showed high accuracy in the prediction, with GLM Boosting achieving the best performance, making it a promising tool for assessing the feasibility of e-payment systems for MSMEs.

Future research could expand on this study by including a larger and more diverse sample of MSMEs across other regions or countries to enhance the generalizability of the findings. Additionally, further exploration of the impact of demographic factors, such as age, education, and business size, on the adoption of e-payment could provide deeper insights. Future studies may also investigate the role of technological infrastructure and regulatory frameworks in the successful implementation of e-payment systems.

ACKNOWLEDGMENT

This research was supported by the Ministry of Education, Technology, and Science, Indonesia namely Kemdiktisaintek Indonesia through Fundamental Research Project 2024 with contract-id-no 459/E5/PG.02.00/2024,104/E5/PG.02.00/2024 1129/LL2/KP/PL/2024; 04/01.02/LPPM/VI/2024.

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