Vol. 8, No. 4, August 2026

ISI Journal of Information Systems and Informatics

Published By Asosiasi Doktor Sistem Informasi Indonesia

Comparative Machine Learning Models for Predicting SME Business Performance

Azizah[1], Rahmat Gernowo[2], Budi Warsito[3], Jumi[4]

[1]Doctoral Program of Information Systems, School of Postgraduate Studies, Universitas Diponegoro, Indonesia
[2]Department of Physics, Faculty of Science and Mathematics, Universitas Diponegoro, Semarang, Indonesia
[3]Department of Statistics, Faculty of Science and Mathematics, Universitas Diponegoro, Indonesia
[4] Department of Business Administration, Politeknik Negeri Semarang, Indonesia

Received:
February 28, 2026
Revised:
June 18, 2026
Accepted:
August 4, 2026
Published:
August 29, 2026

Corresponding Author:
Author Name*:
Azizah
Email*:
azizah01@students.undip.ac.id

DOI:
10.63158/journalisi.v8i4.1705

Abstract. Small and Medium Enterprises (SMEs) play an essential role in supporting economic growth, employment creation, and innovation across developing and emerging economies. To maintain competitiveness, SMEs need to improve their business performance by understanding the factors that influence organizational success. Several factors, including risk-taking, open innovation, cost leadership, proactiveness, aggressiveness, and autonomy, contribute to SME performance improvement. This study aims to develop and compare machine learning models for predicting SME business performance using these influencing factors. A dataset containing 283 SME records obtained from the Mendeley Data Repository was used in this study. Four machine learning approaches were evaluated, including Random Forest (RF), XGBoost, Artificial Neural Network (ANN), and ANN optimized using Particle Swarm Optimization (PSO). The models were assessed using regression performance metrics, including the coefficient of determination (R^2), Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and computational execution time. The experimental results indicate that RF achieved the best prediction performance with an R^2 of 0.924, RMSE of 0.120, and MAE of 0.065, demonstrating high predictive accuracy and low error. XGBoost and ANN-PSO also showed competitive performance, while ANN achieved moderate results. Therefore, RF is recommended as an effective model for SME performance prediction. Future studies should employ larger datasets and external validation to improve model generalizability.

Keywords: Small Medium Enterprises; Business Performance; Machine Learning; Random Forest; Prediction

1. INTRODUCTION

The Nowadays, a successful enterprise is often viewed as one that can effectively seize various opportunities, adapt to continuous environmental changes, and achieve superior results. Business performance is commonly regarded as a measure of an organization's outcomes and overall effectiveness. In the field of business performance and, predictive analytics is one of crucial tool in business decision making, enabling companies to forecast trends, optimize strategies, and enhance profitability [1]. Organizations must be capable of deriving meaningful insights from enterprise data in order to maintain a competitive advantage. Machine learning (ML) models play a vital role in forecasting sales trends, customer behavior, and operational risks [2]. Nevertheless, identifying the most suitable predictive model remains difficult because dataset characteristics and model performance differ. Prior studies have highlighted the importance of choosing the most appropriate ML technique according to business goals and data complexity [3]. Although strategic orientation and entrepreneurial orientation have been widely examined as determinants of SME performance, most studies have relied on traditional statistical methods rather than machine learning approaches. Furthermore, comparative evidence on the predictive performance of different machine learning regression models using these factors remains limited, highlighting an important research gap [4], [5].

The objective of this comparative analysis is to assess four ML algorithms for predicting business insights: Random Forest (RF), eXtreme Gradient Boost (XGBoost), Artificial Neural Network (ANN), and ANN with Particle Swarm Optimization (PSO). RF can efficiently manage high dimensional business data because of its ensemble learning mechanism. In contrast, XGBoost is a competitive method for sales prediction, as it improves overall model effectiveness by enhancing weak learners [6].

Unlike previous studies that concentrated on individual algorithms [7], this research offers a more comprehensive evaluation by emphasizing the strengths and limitations of different models across diverse business applications. It also addresses the significance of data preprocessing and model interpretability, as these elements strongly influence business decision-making processes [8]. This study is primarily managerial prediction and decision-support development, aims to develop and evaluate machine learning models that can accurately predict SME business performance based on strategic and entrepreneurial orientation factors, enabling managers to make more informed, data-driven decisions. Although previous studies have confirmed that entrepreneurial orientation and strategic factors influence SME performance, most research has focused on explaining these relationships using conventional statistical techniques such as regression or SEM. More recent studies have introduced machine learning for firm-performance prediction; however, comparative evidence evaluating multiple regression algorithms using the same SME dataset and predictor variables remains limited. Furthermore, many studies investigate only a single algorithm, making it difficult to determine which model provides the best predictive accuracy and computational efficiency for practical SME decision support.

2. METHODS

2.1 Literature Review

The growing number of studies related to business performance further highlights the importance of this issue. Performance management can be defined as an approach to managing and motivating employees through targets that are primarily based on quantitative performance indicators [1]. Several key factors such as risk-taking, open innovation, cost leadership, proactiveness, aggressiveness, and autonomy have a relation with business performance. Risk taking refers to a firm's willingness to commit significant resources to opportunities with uncertain outcomes and potentially high returns [9]. Open innovation is defined as the purposive use of knowledge inflows and outflows across organizational boundaries to accelerate innovation and create value [10]. Cost leadership represents a competitive strategy through which firms seek to achieve superior performance by minimizing operational costs while maintaining acceptable quality [11]. Proactiveness reflects a firm's forward-looking perspective characterized by anticipating and exploiting future market opportunities ahead of competitors, whereas aggressiveness refers to a firm's tendency to directly and intensely challenge competitors to improve its market position and autonomy denotes the degree of independence granted to individuals or teams to develop and implement entrepreneurial initiatives [12]. Firm performance refers to the extent to which a firm achieves its strategic and operational objectives, commonly measured through indicators such as profitability, sales growth, market share, customer satisfaction, and overall business success [13]. Collectively, these constructs are recognized as important determinants of

SME competitiveness and long-term sustainability. Study reveals a significant positive affect of risk taking propensity on business performance [14], [15]. Many research show that open innovation are positevly associated with business perfromance [16], [17], [18]. Cost leadership has a strong positive correlation with SME performance [19], [20]. Proactiveness is a significant predictor of business performance. Firms that adopt proactive strategies tend to achieve better outcomes, particularly in dynamic environments where adaptability and foresight are critical [21], [22]. Competitive aggressiveness can positively influence performance under certain conditions. For example, firms with specialized technological resources and strong alliance networks benefit more from aggressive strategies [23]. Similarly, in industries with high rates of change, competitive aggressiveness has a stronger positive effect on performance [24]. Autonomy can positively influence firm performance, particularly decision-making autonomy positively impacts organizational performance and technological innovation, mediated by factors like information management culture [25]. Autonomy fosters employee engagement and innovative behavior, which are critical for organizational success [26].

These selected factors are theoretically relevant to SME business performance because they reflect key dimensions of entrepreneurial orientation and strategic behavior that directly influence how firms create and sustain competitive advantage[1], [23]. Risk-taking, proactiveness, and competitive aggressiveness capture a firm's willingness to pursue opportunities under uncertainty, respond to environmental changes, and compete effectively in dynamic markets, all of which are critical for SMEs operating with limited resources [14], [15]. Open innovation and autonomy enhance knowledge sharing, creativity, and employee empowerment, enabling SMEs to improve adaptability and innovation capacity [16], [17], [18], [25], [26]. Meanwhile, cost leadership strengthens operational efficiency and cost control, which are essential for maintaining profitability in resource-constrained environments [19], [20]. Collectively, these factors explain both the strategic posture and internal capabilities of SMEs that shape their overall performance outcomes.

International authors and their research findings have contributed valuable insights to the area of business performance. Many of these studies focus on the relationship between business performance and factors such as corporate strategy, as well as strategic decision-making tools designed to support performance [27], [28]. In addition to the above-mentioned factors, business performance can affect other particular parameters, such as the influence of company location, size, capital structure, legal status, size or turnover. From a complex perspective, size, capital structure, legal status, size or turnover. From a complex perspective, recognizing all factors that affect performance is important.

Recent breakthroughs have generated substantial interest in the use of predictive analytics through machine learning methods for financial growth and management. As a result, modern enterprises need advanced tools to enhance decision-making processes while operating efficiently within the financial sector [29]. Numerous studies have used deep learning models, particularly neural networks, due to their ability to capture nonlinear patterns in financial time-series data, which often results in more accurate forecasts compared to other models[30].

Another important area that has received relatively limited attention from researchers is risk management. With the growing availability of large volumes of data and multiple influencing factors, financial risk detection and management have undergone significant transformation. Among the methods increasingly considered for this purpose is deep learning [31] Its applications extend beyond predicting credit defaults and market volatility to identifying broader systemic risks. Current research also explores whether predictive analytics can improve portfolio planning and optimization. In this context, ML models contribute to the development of more effective asset allocation algorithms that evaluate various financial products. It has been suggested that data-driven financial planning supported by ML can increase returns by improving risk management and enabling higher profitability and impact to business performance [32].

2.2 Research Workflow

The proposed methodology involves four ML methods namely RF, XGBoost, ANN and ANN with PSO are thoroughly compared using a commercial dataset. The first step is business performance data gathering, which includes variables such as risk-taking, open innovation, cost leadership, proactiveness, aggressiveness, and autonomy. This data will be preprocessed to ensure quality and consistency. Preprocessing is done on the dataset to improve model performance. This includes data cleaning and normalization. Normalization, missing values imputation and transformation are required to prepare the

ISI Journal of Information Systems and Informatics
Published By Asosiasi Doktor Sistem Informasi Indonesia

data for use by ML models. A structured dataset is collected, cleaned, and preprocessed, followed by feature engineering to enhance model performance. Each algorithm is trained and optimized using hyperparameter tuning techniques to ensure optimal accuracy and efficiency. Figure 1 illustrates the stages of the ML framework in predicting SME Performance.

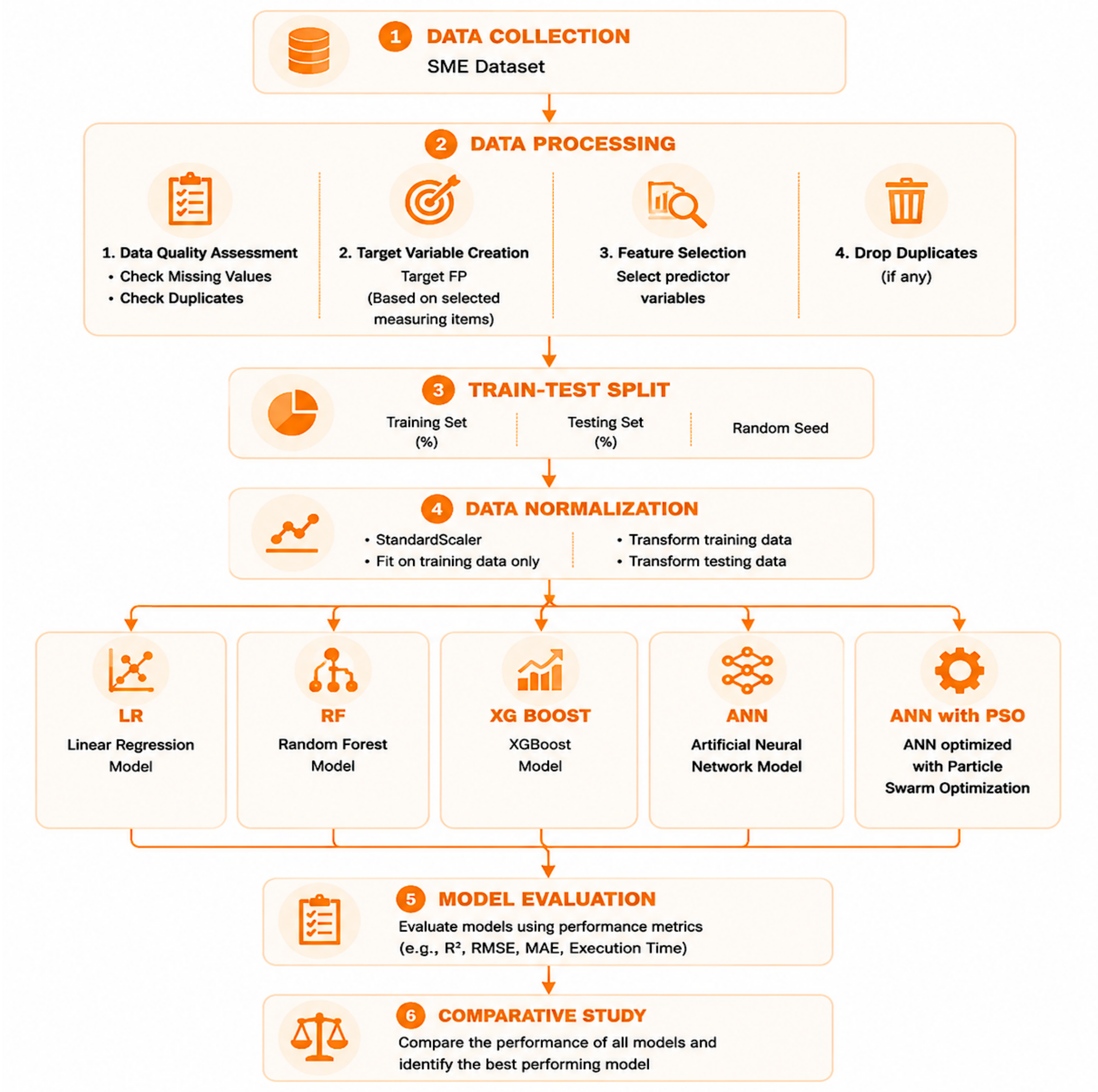

Figure 1. SME Performance prediction model framework

2.3 Data Collection

This study collected a dataset on the relationship between risk taking, open innovation, cost leadership, proactiveness, aggressiveness, autonomy and performance in SMEs. A dataset is used with the title Dataset of relationship of Entrepreneurship Orientation, Open Innovation and Cost Leadership towards Firm Performance among Small Medium Enterprises (SMEs) in Malaysia which is taken from Mendeley data [33].

The dataset was collected from Small and Medium Enterprises (SMEs) in Malaysia. SMEs constitute a major component of the Malaysian economy and significantly contribute to employment generation, innovation activities, and national economic growth. The dataset was developed to examine how entrepreneurial orientation dimensions, open innovation practices, and cost leadership strategies influence firm performance in Malaysian SMEs. All latent construct items in the dataset were measured using a five-point Likert scale, where respondents indicated their level of agreement with each statement ranging from 1 = strongly disagree, 2 = disagree, 3 = neutral, 4 = agree, and 5 = strongly agree.

2.4 Data Preprocessing

Data quality assessment showed that the dataset had no missing values, no duplicate records, and therefore no records were removed. As a result, all 283 records were used in the machine learning experiments. The target variable, MeanFP, represents the average score of the questionnaire items measuring the Firm Performance construct. Each predictor variable (MeanA, MeanCA, MeanCL, MeanOI, MeanP, and MeanRT) was calculated independently from its corresponding construct items. The Firm Performance items used to compute MeanFP were not included among the predictor variables, ensuring that the input features were completely independent of the prediction target and preventing target leakage.

2.5 Data Normalization

Data normalization is performed to place all dataset values within the same range, rather than different ranges. This method can improve dataset quality. This study used the Standard Scaler (SS) method.

$$z = \frac{X-\mu}{\sigma} \tag{1}$$

where:

z= standardized value (normalized score),

X= original value of the observation,

μ= mean value of the corresponding variable,

σ= standard deviation of the corresponding variable.

ISI Journal of Information Systems and Informatics
Published By Asosiasi Doktor Sistem Informasi Indonesia

StandardScaler was employed to standardize all predictor variables by transforming them to have a mean of zero and a standard deviation of one. The scaler was fitted exclusively on the training dataset, and the learned parameters were subsequently applied to transform the testing dataset, thereby preventing information leakage and ensuring an unbiased evaluation of model performance. Outliers were not removed from the dataset. During preprocessing, duplicate records were removed and predictor variables were standardized using the StandardScaler technique. Standardization transforms the variables to have a mean of zero and a standard deviation of one, thereby reducing the influence of scale differences among variables. Since the dataset was derived from Likert-scale survey responses (1–5) and no extreme observations were detected during preliminary inspection, all observations were retained for model training and evaluation.

2.6 Data Training and Testing

The dataset was divided into training and testing subsets to evaluate the predictive performance of the proposed machine learning models. An 80:20 data splitting strategy was applied, where 80% of the samples were used for model training and 20% were used for testing. The data partitioning process was performed using a random state of 42 to ensure reproducibility across all experiments.

2.7 Machine Learning Models

This study employed five machine learning models to predict SME business performance, including Linear Regression (LR), Random Forest (RF), eXtreme Gradient Boosting (XGBoost), Artificial Neural Network (ANN), and Artificial Neural Network optimized using Particle Swarm Optimization (ANN-PSO). These models were selected to represent different learning approaches, including statistical regression, ensemble learning, deep learning, and hybrid optimization-based learning.

2.7.1 Linear Regression (LR)

Linear Regression (LR) is a statistical and machine learning approach that estimates the relationship between independent variables and a continuous dependent variable by fitting a linear function [34]. The mathematical formulation of LR is expressed in Equation (2).

$$Y = a + \sum_{i=1}^{n} b_i X_i \tag{2}$$

ISI Journal of Information Systems and Informatics
Published By Asosiasi Doktor Sistem Informasi Indonesia

where Yrepresents the predicted SME performance score, $X_i$represents the input variables, $a$is the intercept value, and $b_i$represents the regression coefficient of each independent variable. The LR prediction workflow consists of data input, model training, and output prediction, as illustrated in Figure 2. LR was implemented as a baseline model to compare the performance of more complex machine learning algorithms.

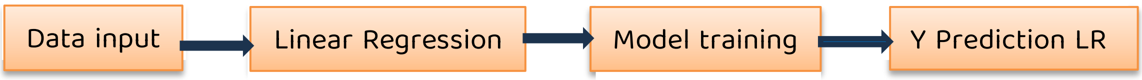

Figure 2. Linear Regression prediction model

2.7.2 Random Forest (RF)

Random Forest (RF) is an ensemble learning algorithm that combines multiple decision trees to improve prediction performance and reduce model variance [35]. The final prediction is generated by aggregating the outputs from individual decision trees, as shown in Equation (3).

$$\hat{Y} = \frac{1}{N}\sum_{i=1}^{N} T_i\,(X) \tag{3}$$

where $\hat{Y}$represents the predicted value generated by RF, Ndenotes the number of decision trees, and $T_i(X)$represents the prediction generated by the i-th decision tree for input vector X.

The RF prediction process, including data input, tree construction, ensemble prediction, and final output generation, is presented in Figure 3. The RF model was implemented using the RandomForestRegressor algorithm from Scikit-learn with 100 decision trees ($n\_estimators = 100$) and a random state of 42. Other parameters were maintained using default settings, including unlimited maximum tree depth, minimum samples split of 2, and minimum samples leaf of 1. The model was developed using Python with Scikit-learn, Pandas, NumPy, and Matplotlib.

Figure 3. Random Forest prediction model

2.7.3 XGBoost

XGBoost is a gradient boosting-based machine learning algorithm that constructs multiple decision trees sequentially, where each new tree improves the prediction errors of previous learners [36]. The prediction function of XGBoost is defined in Equation (4).

$$\hat{Y} = \sum_{i=1}^{N} f_i\,(X) \qquad (4)$$

where $\hat{Y}$represents the final prediction, $N$is the number of base learners, and $f_i(X)$denotes the prediction contribution of the i-th decision tree.

The XGBoost prediction workflow is illustrated in Figure 4, showing the process from feature input, boosting iterations, and final prediction generation. The XGBoost Regressor was configured with 100 estimators, a learning rate of 0.1, maximum tree depth of 3, and random state of 42. These parameters were selected to achieve a balance between predictive capability and overfitting prevention. The model implementation utilized Python libraries including XGBoost, Scikit-learn, Pandas, NumPy, and Matplotlib.

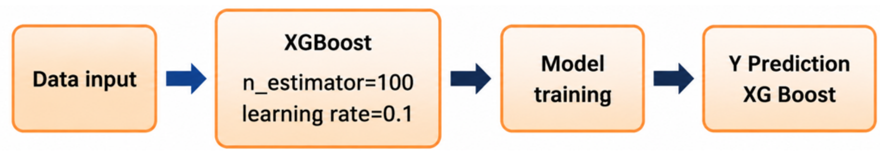

Figure 4. XGBoost prediction model

2.7.4 Artificial Neural Network (ANN)

Artificial Neural Network (ANN) is a machine learning method inspired by biological neural systems that learns complex patterns through interconnected neurons [37]. ANN is capable of modeling nonlinear relationships between input variables and output values. The mathematical representation of a neuron computation is expressed in Equation (5).

$$y = f(\sum_{i=1}^{n} w_i\,x_i + b) \qquad (5)$$

where $y$represents the neuron output, $w_i$denotes the weight of input variable x_i, $b$represents the bias value, and $f$is the activation function.

The ANN prediction architecture consisting of input, hidden, and output layers is illustrated in Figure 5. The ANN model was developed using TensorFlow and Keras with six input neurons, two hidden layers containing 16 and 8 neurons, and one output neuron for regression prediction. The ReLU activation function was applied to hidden layers, while the output layer used linear activation. The model was trained using the Adam optimizer with Mean Squared Error (MSE) loss for 100 epochs and a batch size of 8. A validation split of 20% was applied during training.

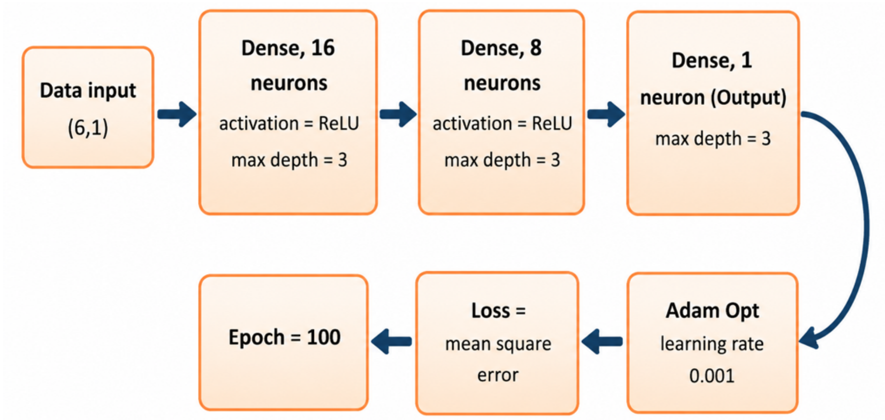

Figure 5. ANN prediction model

2.7.5 Artificial Neural Network with Particle Swarm Optimization (ANN-PSO)

ANN-PSO is a hybrid machine learning approach that integrates ANN capability in modeling nonlinear relationships with PSO optimization for selecting optimal network parameters [38]. In this approach, each particle represents a candidate ANN configuration, and the optimization process searches for the parameter combination with minimum prediction error. The velocity update mechanism of PSO is represented in Equation (6).

$$v_i^{t+1} = wv_i^t + c_1r_1(p_i - x_i^t) + c_2r_2(g - x_i^t) \quad (6)$$

where $v_i$represents particle velocity, $w$is the inertia weight, $c_1$and $c_2$are acceleration coefficients, $r_1$and $r_2$are random values, $p_i$represents the personal best position, and $g$represents the global best position.

The ANN-PSO prediction workflow is presented in Figure 6, describing the interaction between PSO optimization and ANN prediction. The ANN-PSO optimization process searched for the optimal number of neurons in hidden layers and learning rate. PSO was

ISI Journal of Information Systems and Informatics
Published By Asosiasi Doktor Sistem Informasi Indonesia

configured with 10 particles and 20 iterations. The search space included 8–64 neurons for the first hidden layer, 4–32 neurons for the second hidden layer, and learning rates between 0.0001 and 0.01. The fitness function was defined using Mean Squared Error (MSE) calculated from prediction results. The optimal ANN configuration obtained from PSO consisted of 31 neurons in the first hidden layer, 16 neurons in the second hidden layer, and a learning rate of 0.00942. The optimized ANN model was subsequently trained for 100 epochs and evaluated using R^2, RMSE, and MAE metrics. The implementation was performed using Python with TensorFlow, Keras, PySwarms, Scikit-learn, Pandas, NumPy, and Matplotlib.

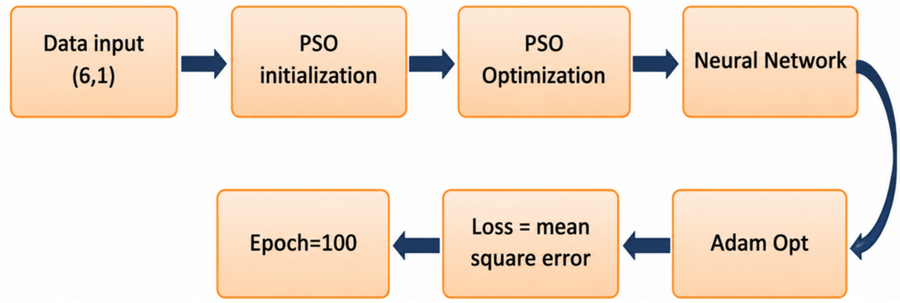

Figure 6. ANN prediction model with PSO

3. RESULT AND DISCUSSION

3.1. Performance Evaluation

The next stage of this study is to assess and compare four ML models for predicting SME performance. In the evaluation stage, this study uses regression metrics such as R2 (R-squared), RMSE (Root Mean Squared Error), MAE (Mean Absolute Error) and execution time. This dataset has 283 rows of data to be processed. The data is divided into 80% training and 20% testing. Table 2 shows a description of the dataset.

Table 2. Description of the SME Performance dataset

	MeanA	MeanCA	MeanCL	MeanOI	MeanP	MeanRT	MeanFP
Count	283	283	283	283	283	283	283
Mean	3.923	3.435	3.983	3.330	4.069	3.711	4.152
Std	0.597	0.747	0.585	0.813	0.495	0.835	0.567
Min	1.4	1.8	2.2	1.0	2.8	1.6	2.0
25%	4.0	3.0	3.8	2.8	3.6	3.4	4.0

ISI Journal of Information Systems and Informatics

Published By Asosiasi Doktor Sistem Informasi Indonesia

	MeanA	MeanCA	MeanCL	MeanOI	MeanP	MeanRT	MeanFP
50%	4.0	3.6	4.0	3.6	4.2	4.0	4.6
75%	4.2	4.0	4.4	3.8	4.4	4.4	4.6
Max	5.0	4.6	4.8	4.6	5.0	4.6	4.8

Table 2 shows the number of datasets, the average, minimum, and maximum. The average value for each variable is in a fairly high range, between 3,330 and 4,152. The relatively small standard deviation, around 0.495 and 0.835, indicates that the data distribution is not too large. The minimum and maximum values indicate variation in respondents' answers. The quartile values (25%, 50%, and 75%) range from 3 to 4.6, indicating that the majority of the data is concentrated in the mid-to-high range. Table 3 shows a comparison of the results of the SME performance prediction study using four ML models.

Table 3. Results of the SME Performance model study

Training	RF	XGBoost	ANN	ANN + PSO
R2	0.987	0.963	0.859	0.961
RMSE	0.065	0.114	0.220	0.116
MAE	0.029	0.083	0.164	0.088
Testing	RF	XGBoost	ANN	ANN + PSO
R2	0.924	0.883	0.726	0.872
RMSE	0.120	0.150	0.229	0.156
MAE	0.065	0.098	0.160	0.122

In the training stage the RF model provided the best performance with an R^2 of 0.987 and an RMSE value of 0.065 and an MAE of 0.029, which are very low, indicating excellent ability to learn data, although it has the potential to experience overfitting. The XGBoost model also showed excellent performance with an R^2 of 0.963 and a relatively small error, slightly below RF. Meanwhile, ANN performed quite well with an R^2 of 0.859. After optimization using PSO (ANN with PSO), performance increased significantly with an R^2 of 0.961 and a decrease in RMSE and MAE values, indicating that parameter optimization was able to improve the model's accuracy in predicting training data.

ISI Journal of Information Systems and Informatics
Published By Asosiasi Doktor Sistem Informasi Indonesia

Based on the data from the testing phase, it can be seen that the model performance also varies in predicting data. The RF model showed the best performance with an R^2 value of 0.924, meaning it was able to explain approximately 92.4% of the data variation. The XGBoost and ANN with PSO models also showed good performance with R^2 values of 0.883 and 0.872, respectively, but both models were still below RF. Next was ANN, which had adequate performance with an R^2 value of 0.726. In terms of prediction error, the RF model had the smallest error values for both RMSE and MAE. The RMSE value of 0.120 and MAE of 0.065 indicated that the resulting predictions were close to the actual values. This indicates that the difference between the predicted and actual values is very small and stable. The XGBoost and ANN with PSO models had higher error rates, but were still in the good and acceptable category. ANN had a larger error, indicating that this model was not yet able to learn data patterns optimally.

To evaluate model robustness and stability, a 5-fold cross-validation procedure was conducted for the LR model. As presented in Table 4, the baseline model achieved an average R^2 of 0.3504 ± 0.1821, RMSE of 0.4232 ± 0.0461, and MAE of 0.3460 ± 0.0299. Linear Regression exhibited substantially lower predictive accuracy and higher prediction errors. During the five-fold cross-validation procedure, preprocessing was performed independently within each fold. Specifically, the StandardScaler was fitted only on the training partition of each fold, and the learned scaling parameters were subsequently applied to the corresponding validation partition. This leakage-safe preprocessing strategy ensured that no information from the validation data was used during model training or preprocessing.

Table 4. Linear Regression Stability Assessment Using 5-Fold Cross Validation

Fold	R^2	RMSE	MAE
1	0.1847	0.3945	0.3308
2	0.0806	0.3738	0.3189
3	0.4629	0.4437	0.3456
4	0.5322	0.5035	0.4034
5	0.4914	0.4006	0.3315
Mean ± SD	0.3504 ± 0.1821	0.4232 ± 0.0461	0.3460 ± 0.0299

For RF the model achieved an average R^2 of 0.9372 ± 0.0277, an average RMSE of 0.1321 ± 0.0495, and an average MAE of 0.0711 ± 0.0191 as shown in Table 5. The relatively small standard deviations indicate that the predictive performance remained stable across different folds. Furthermore, the high mean R^2 demonstrates that the model consistently explained a substantial proportion of the variance in SME performance, while the low RMSE and MAE values indicate accurate predictions.

Table 5. Random Forest Stability Assessment Using 5-Fold Cross Validation

Fold	R^2	RMSE	MAE
1	0.9307	0.1150	0.0660
2	0.9124	0.1154	0.0663
3	0.9546	0.1291	0.0694
4	0.9069	0.2246	0.1062
5	0.9816	0.0763	0.0478
Mean ± SD	0.9372 ± 0.0277	0.1321 ± 0.0495	0.0711 ± 0.0191

For the XGBoost model as shown in Table 6, the model achieved an average R^2 of 0.8989 ± 0.0367, an average RMSE of 0.1694 ± 0.0541, and an average MAE of 0.1157 ± 0.0231. The relatively small standard deviations across the five folds indicate that the XGBoost model maintained reasonably consistent predictive performance. The high mean R^2 of 0.8989 demonstrates that the model consistently explained approximately 89.9% of the variance in SME performance, confirming its effectiveness in capturing the underlying patterns in the data. The low RMSE and MAE values further indicate that the model produced accurate predictions with minimal errors.

Table 6. XGBoost Stability Assessment Using 5-Fold Cross Validation

Fold	R^2	RMSE	MAE
1	0.8828	0.1496	0.0984
2	0.8685	0.1414	0.1107
3	0.9480	0.1380	0.1061
4	0.8582	0.2773	0.1611
5	0.9373	0.1407	0.1020
Mean ± SD	0.8989 ± 0.0367	0.1694±0.0541	0.1157±0.0231

ISI Journal of Information Systems and Informatics
Published By Asosiasi Doktor Sistem Informasi Indonesia

For ANN model as shown in Table 7, the model achieved an average R^2 of 0.7313 ± 0.2536, an average RMSE of 0.2425 ± 0.0565, and an average MAE of 0.1795 ± 0.0398. The relatively large standard deviations, particularly for R^2, indicate that the predictive performance varied considerably across different folds. While the mean R^2 of 0.7313 demonstrates that the model can explain a moderate proportion of the variance in SME performance on average, the substantial performance inconsistency across folds raises concerns about its generalizability. Specifically, fold 2 exhibited exceptionally poor performance, while Folds 4 and 5 achieved relatively good results.

Table 7. ANN Stability Assessment Using 5-Fold Cross Validation

Fold	R^2	RMSE	MAE
1	0.8253	0.1826	0.1431
2	0.2259	0.3430	0.2505
3	0.8428	0.2401	0.1872
4	0.8838	0.2510	0.1759
5	0.8785	0.1958	0.1409
Mean ± SD	0.7313 ± 0.2536	0.2425 ± 0.0565	0.1795 ± 0.0398

As presented in Table 8, model ANN-PSO achieved an average R^2 of 0.8581 ± 0.0260, an average RMSE of 0.2079 ± 0.0632, and an average MAE of 0.1538 ± 0.0423. The small standard deviation of the R^2 values indicates that the model produced consistent predictive performance across different folds. These findings demonstrate that the ANN-PSO model is reasonably stable and capable of providing reliable predictions of SME performance across different data partitions.

Table 8. ANN-PSO Stability Assessment Using 5-Fold Cross Validation

Fold	R^2	RMSE	MAE
1	0.8512	0.1685	0.1299
2	0.8874	0.1308	0.0954
3	0.8497	0.2347	0.1581
4	0.8170	0.3150	0.2237
5	0.8850	0.1905	0.1617
Mean ± SD	0.8581 ± 0.0260	0.2079 ± 0.0632	0.1538 ± 0.0423

As shown in Table 9, the Random Forest model achieved the best overall performance, obtaining the highest average R^2 and the lowest prediction errors. XGBoost ranked second with an average R^2 of 0.8989 ± 0.0367, followed by ANN-PSO and ANN. In terms of stability, ANN-PSO exhibited a substantially lower standard deviation of R^2 compared with ANN, indicating that the Particle Swarm Optimization algorithm successfully improved the consistency of neural network predictions across different folds. However, despite this improvement, ANN-PSO did not surpass the predictive accuracy of Random Forest or XGBoost. Overall, the results demonstrate that ensemble-based models, particularly Random Forest, provide superior predictive performance and stability for SME performance prediction.

Table 9. Comparison of Model Stability Using 5-Fold Cross Validation

Model	R^2 (Mean ± SD)	RMSE (Mean ± SD)	MAE (Mean ± SD)
Linear Regression (Baseline)	0.3504 ± 0.1821	0.4232 ± 0.0461	0.3460 ± 0.0299
Random Forest	0.9372 ± 0.0277	0.1321 ± 0.0495	0.0711 ± 0.0191
XGBoost	0.8989 ± 0.0367	0.1694 ± 0.0541	0.1157 ± 0.0231
ANN	0.7313 ± 0.2536	0.2425 ± 0.0565	0.1795 ± 0.0398
ANN-PSO	0.8581 ± 0.0260	0.2079 ± 0.0632	0.1538 ± 0.0423

Considering that the SME performance variable was measured on a 1–5 Likert scale, the obtained RMSE and MAE represent only 2.71% and 1.46% of the total scale range, respectively. Therefore, the prediction errors are relatively small, indicating that the model can estimate self-reported SME performance with a high level of accuracy. To further evaluate the reliability of the best-performing model, a residual analysis was conducted for the RF model. The residual statistics are presented in Table 9. The model produced a mean residual of 0.0059 and a median residual close to zero, indicating that the prediction errors were generally unbiased and centered around the actual values. The standard deviation of the residuals was 0.1083, suggesting a relatively small dispersion of prediction errors. In addition, the mean absolute error was 0.0584, confirming that the average prediction error remained low. The residual distribution exhibited a negative skewness value of -1.5216, indicating that larger errors occurred more frequently on the negative side of the distribution. Furthermore, the kurtosis value of 7.8275 suggests a leptokurtic distribution with heavier tails than a normal distribution, implying the presence of a limited number of relatively large prediction errors. Nevertheless, the

ISI Journal of Information Systems and Informatics
Published By Asosiasi Doktor Sistem Informasi Indonesia

overall residual magnitude remained small, as evidenced by the low RMSE (0.1084) and MAE (0.065) values. These findings indicate that the RF model provides accurate and reliable predictions for SME performance while maintaining a low level of prediction error. Table 10 shows residual statistics of the RF model.

Table 10. Residual Statistics of the Random Forest Model

Statistic	Value
Mean Residual	0.0059
Std Residual	0.1083
Median Residual	0.0000
Min Residual	-0.5100
Max Residual	0.2340
Mean Absolute Error	0.0584
Skewness	-1.5216
Kurtosis	7.8275

The RF model has a point distribution closest to the diagonal line, indicating accurate and consistent predictions. XGBoost and ANN with PSO are also quite dense around the line, but there are still deviations. The ANN model shows a wider point distribution, indicating a higher level of prediction error. Comparison of the actual values and predicted values of the four models, in the form of a scatter plot with a diagonal line as a prediction reference, can be seen in Figure 10.

The RF model has a point distribution closest to the diagonal line, indicating accurate and consistent predictions. XGBoost and ANN with PSO are also quite dense around the line, but there are still deviations. The ANN model shows a wider point distribution, indicating a higher level of prediction error. In addition to the scatterplot, the comparison between the actual and predicted values of the four models is also displayed in a line graph against the observed data. This can be seen in Figure 11.

The RF model has a predicted line that most consistently follows the actual line pattern, demonstrating very high accuracy with small deviations. The XGBoost and ANN with PSO models demonstrates good ability to follow data fluctuations, although some deviations

ISI Journal of Information Systems and Informatics
Published By Asosiasi Doktor Sistem Informasi Indonesia

are visible. Meanwhile, the ANN shows a more visible difference between the actual and predicted values, especially at some extreme points.

Execution time was measured using Python's time module by recording the elapsed time required for model training and prediction. All experiments were conducted in the Google Colab environment using an Intel® Xeon® CPU running at 2.20 GHz. The implementation was performed in Python 3.12 with Scikit-learn 1.6.1, TensorFlow 2.20.0, XGBoost 3.2.0, NumPy 2.0.2, and Pandas 2.2.2. To minimize the impact of random fluctuations and system workload variations, each machine learning model was executed five independent times under identical conditions, and the average execution time was reported. This study also compared the execution time of each ML prediction model. The results of this comparison are presented in Table 11.

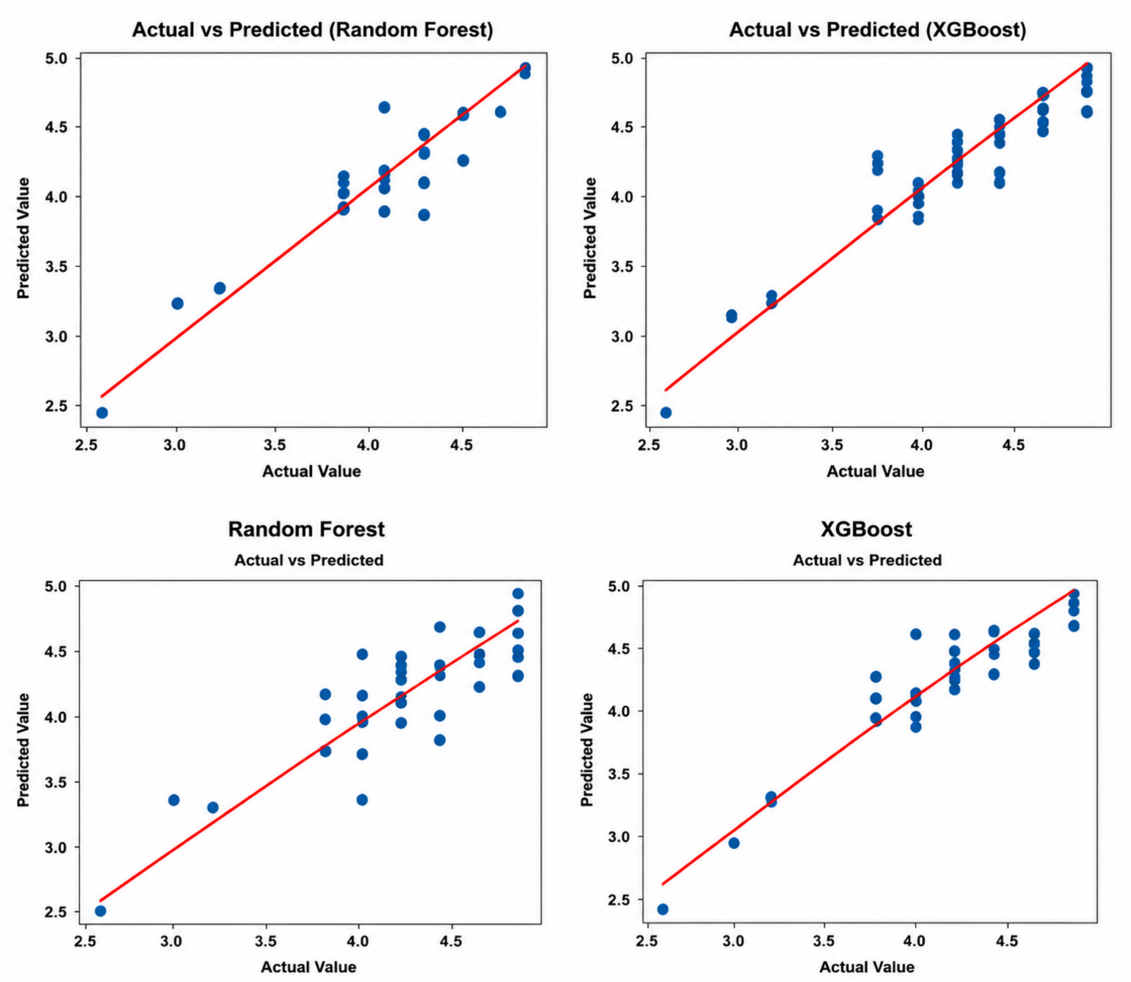

Figure 10. Scatter plot comparing the actual and predicted values of the four models.

ISI Journal of Information Systems and Informatics
Published By Asosiasi Doktor Sistem Informasi Indonesia

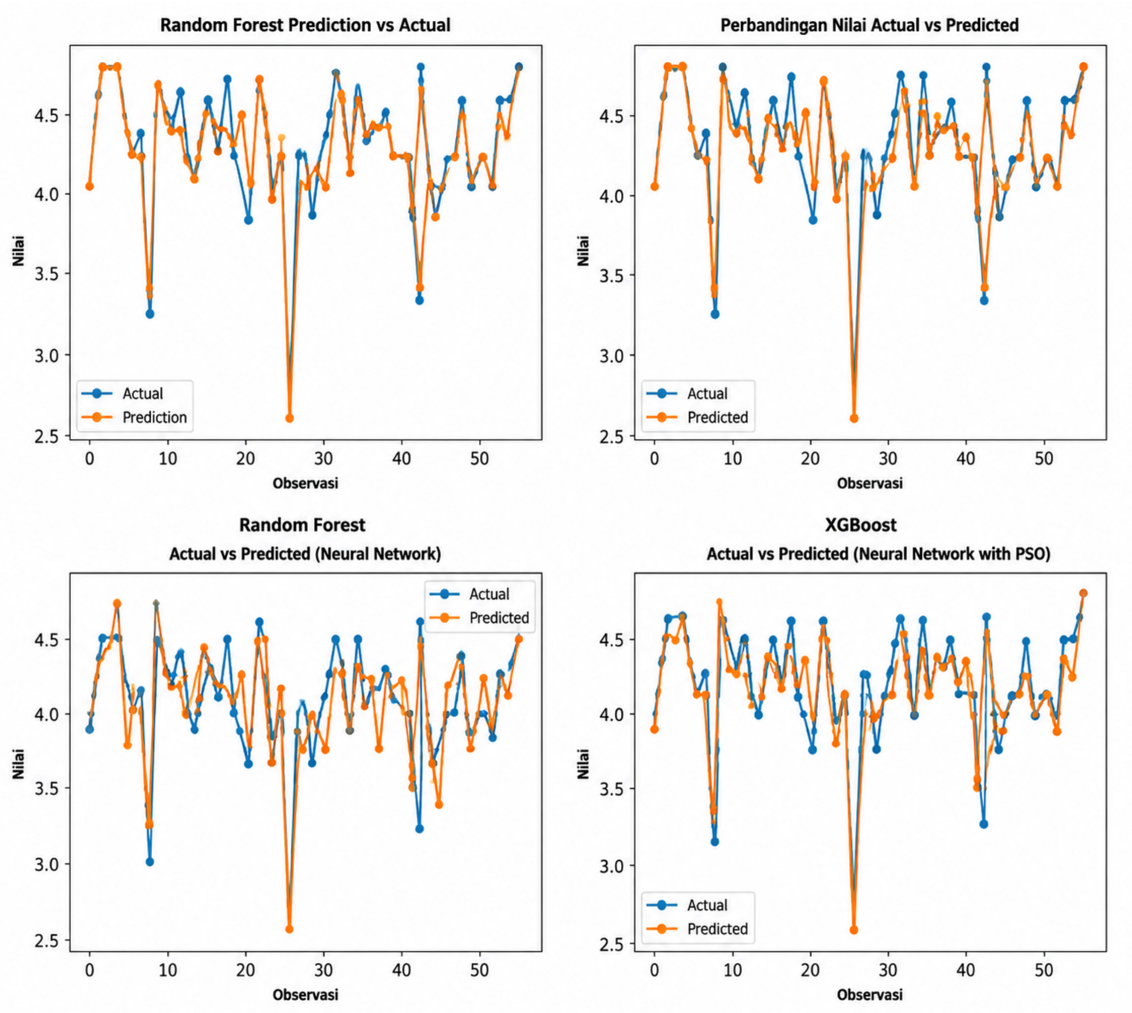

Figure 11. Line graph comparing actual and predicted values of the four models.

Table 11. Execution time of SME Performance prediction model

	LR	RF	XGBoost	ANN	ANN with PSO
Avg Execution Time	14 second	6 second	10 second	31 second	10 minute 14 second

For a comparison of computational time, RF is the fastest model with an average execution time of only 6 seconds, followed by XGBoost at 10 seconds and ANN at 31 seconds, which is still relatively fast. The ANN with PSO model has the highest execution time, which is more than 10 minutes, due to the iteration-based optimization process in PSO.

ISI Journal of Information Systems and Informatics
Published By Asosiasi Doktor Sistem Informasi Indonesia

Although the Random Forest model achieved the highest predictive performance, the possibility of overfitting was evaluated using 5-fold cross-validation and residual analysis. The model maintained consistently high performance across folds, indicating good stability and generalization capability. Moreover, the residual analysis showed low prediction errors and residuals centered near zero, suggesting unbiased predictions. Therefore, despite its high accuracy, there is limited evidence of severe overfitting in the Random Forest model.

The superior performance of RF over ANN in this study is likely due to the relatively small dataset, for which RF is better suited because it effectively captures nonlinear relationships while reducing overfitting through ensemble learning. In contrast, ANN generally requires larger datasets to optimize its numerous parameters effectively. Although ANN with PSO improved the predictive accuracy of the conventional ANN by optimizing network weights and reducing the risk of convergence to local optima, this improvement came at the cost of substantially longer execution time due to the iterative optimization process performed by PSO.

To examine whether the differences in predictive performance among the models were statistically meaningful, a Wilcoxon signed-rank test was performed using the R^2 values obtained from the 5-fold cross-validation. Although the Random Forest model consistently achieved the highest mean R^2, the pairwise comparisons between Random Forest and the other models did not reach statistical significance, all $p = 0.0625$. This result is likely attributable to the limited number of cross-validation folds with $n = 5$, which reduces the statistical power of the test. Therefore, while Random Forest demonstrated superior average predictive performance, the observed differences should be interpreted with caution and require confirmation using larger datasets or more extensive validation procedures.

The comparative results indicate that ensemble learning methods, particularly Random Forest, are more effective than neural network-based approaches for predicting SME business performance from questionnaire-based data. Random Forest consistently achieved the highest predictive accuracy in both the hold-out testing and 5-fold cross-validation experiments while maintaining relatively low computational cost, suggesting that the relationships among entrepreneurial orientation variables and business

ISI Journal of Information Systems and Informatics
Published By Asosiasi Doktor Sistem Informasi Indonesia

performance are nonlinear but can be effectively captured through ensemble decision trees. Although ANN with PSO improved the predictive capability of the conventional ANN, its substantial computational overhead indicates that optimization alone cannot compensate for the limitations imposed by a relatively small dataset. These findings are consistent with previous studies reporting that tree-based ensemble algorithms generally outperform deep learning models when sample sizes are limited and predictor variables consist of structured survey data rather than large-scale unstructured data. Furthermore, the consistent importance of Cost Leadership, Aggressiveness, and Open Innovation across both Random Forest and XGBoost suggests that these strategic capabilities are robust predictors of SME performance. This agreement between two independent ensemble models strengthens confidence that these variables contain meaningful predictive information, although the results should be interpreted as predictive rather than causal relationships. Overall, the study demonstrates that selecting an appropriate machine learning algorithm depends not only on predictive accuracy but also on model stability, computational efficiency, and data characteristics. For questionnaire-based SME datasets with relatively small sample sizes, Random Forest provides the most balanced solution for supporting managerial decision-making and business performance prediction.

The findings have practical implications beyond algorithm comparison. The consistent identification of cost leadership, aggressiveness, and open innovation as the most influential predictors suggests that SME managers should prioritize these strategic capabilities to improve business performance. In addition, the RF model can be used as a decision support tool to estimate SME performance and support strategic decision making based on organizational characteristics.

3.2. Discussion

The experimental results demonstrate that machine learning approaches can effectively predict SME business performance based on strategic capability factors, including Cost Leadership, Open Innovation, Aggressiveness, Proactiveness, Risk-Taking, and Competitive Advantage. Among the evaluated models, Random Forest (RF) achieved the highest predictive capability, outperforming XGBoost, ANN, and ANN-PSO in both hold-out testing and cross-validation experiments. The superior performance of RF indicates that SME performance relationships are likely nonlinear and involve complex interactions among multiple strategic factors, which can be effectively captured through ensemble-based decision tree models.

The strong performance of RF can be attributed to its ability to combine multiple decision trees and reduce prediction variance through ensemble learning. Unlike individual regression models that assume linear relationships between variables, RF can identify complex patterns and interactions within structured questionnaire-based datasets. This characteristic is particularly beneficial for SME performance prediction because entrepreneurial and strategic factors often influence organizational outcomes through interconnected mechanisms rather than simple linear relationships. The cross-validation results further confirm the stability of RF, with an average R^2 of 0.9372 ± 0.0277, indicating consistent predictive performance across different data partitions.

Although XGBoost also demonstrated competitive performance, its predictive capability remained slightly below RF. The average cross-validation R^2 of 0.8989 ± 0.0367 indicates that gradient boosting successfully captured important patterns within SME performance data. However, the sequential learning mechanism of XGBoost may be more sensitive to parameter configuration, especially when applied to relatively small datasets. In this study, the dataset consisted of only 283 SME observations, which may limit the ability of boosting algorithms to fully exploit complex patterns compared with RF's randomized ensemble mechanism.

The ANN-based approaches produced different performance characteristics compared with tree-based models. The conventional ANN achieved lower predictive performance, with a testing R^2 of 0.726 and a cross-validation R^2 of 0.7313 ± 0.2536. The relatively high standard deviation indicates instability across different data partitions. This result suggests that ANN may require a larger number of samples to effectively optimize network parameters and avoid sensitivity to training variations. Since the dataset contains structured tabular data rather than large-scale image, text, or sequential information, the advantage of deep learning architectures may not be fully realized.

The integration of PSO improved the performance and stability of ANN by optimizing important network parameters. ANN-PSO achieved higher testing performance compared with conventional ANN, increasing the R^2 value from 0.726 to 0.872. Furthermore, the cross-validation standard deviation of R^2 decreased substantially to 0.0260, demonstrating that PSO improved prediction consistency. However, the improvement in predictive performance was accompanied by a significant increase in computational cost. The execution time of ANN-PSO exceeded 10 minutes, while RF required only approximately 6 seconds. This finding highlights an important trade-off between optimization complexity and practical usability. For SME performance prediction applications, computational efficiency is an important consideration because decision-support systems require models that can provide accurate predictions within reasonable processing time.

The residual analysis of RF further supports its reliability as the preferred model. The residual distribution showed a mean residual close to zero (0.0059), indicating that the model predictions were generally unbiased. The relatively low MAE value and small residual dispersion demonstrate that RF was able to maintain accurate prediction performance across different SME performance levels. Although the residual distribution showed negative skewness and higher kurtosis, indicating the existence of several larger prediction errors, these deviations were limited and did not significantly affect the overall predictive capability of the model.

The feature importance analysis from RF and XGBoost provides additional insights into the factors associated with SME performance prediction. Cost Leadership consistently appeared as the most influential predictor, followed by Aggressiveness and Open Innovation. This finding suggests that SMEs with stronger cost management strategies, competitive actions, and innovation capabilities tend to demonstrate higher predicted performance levels. However, these feature importance values should be interpreted as predictive contributions rather than causal relationships. Further studies using causal modeling approaches, such as structural equation modeling or longitudinal analysis, are required to validate the underlying mechanisms between strategic factors and SME performance.

The statistical comparison using the Wilcoxon signed-rank test showed that differences between RF and other models were not statistically significant ($p = 0.0625$). Although RF achieved the highest average performance, the limited number of cross-validation folds ($n = 5$) may have reduced the statistical power of the analysis. Therefore, the results indicate a practical advantage of RF rather than definitive statistical superiority. Future research should consider larger datasets, repeated cross-validation, or external validation using SMEs from different regions to confirm model robustness and generalizability.

From a managerial perspective, the findings demonstrate that machine learning can support SME decision-making by providing predictive insights into business performance. The RF model can be utilized as a decision-support mechanism to estimate performance levels based on existing organizational characteristics and identify strategic areas requiring improvement. In particular, SMEs may benefit from strengthening cost efficiency, innovation activities, and competitive strategies to enhance their performance potential.

Finally, this study highlights that the selection of an appropriate machine learning model depends not only on prediction accuracy but also on dataset characteristics, computational efficiency, and model stability. For small-scale structured SME datasets, ensemble learning methods, particularly Random Forest, provide a balanced solution by achieving high predictive accuracy with low computational requirements. These findings contribute to the growing application of machine learning in SME analytics and demonstrate the potential of data-driven approaches for supporting strategic business decisions.

4. CONCLUSION

This study compares the performance of LR, RF, XGBoost, ANN, and ANN with PSO in predicting SME performance from questionnaire data. Among the models evaluated, RF demonstrated the highest predictive performance in the current dataset and experimental setup, demonstrating the highest R^2 and lowest prediction error, while maintaining a favorable balance between prediction accuracy and computational efficiency. XGBoost and ANN with PSO also produced competitive results, while the conventional ANN model showed lower prediction accuracy. Importantly, the developed model predicts SME performance, not objective financial performance, therefore, the findings should be interpreted as a prediction of perceived business performance based on respondents' assessments. This study has several limitations, the relatively small dataset size and the lack of external validation with an independent dataset. Future

ISI Journal of Information Systems and Informatics
Published By Asosiasi Doktor Sistem Informasi Indonesia

research should evaluate the proposed model with a larger and more diverse SME dataset, incorporate explainable artificial intelligence techniques to improve the model interpretability, and validate predictions using objective financial and operational performance indicators to enhance the generalizability and practical applicability of the results.

REFERENCES

[1] R. Rajnoha and P. Lesníková, "Strategic performance management system and corporate sustainability concept—Specific parameters in Slovak enterprises," *J. Compet.*, vol. 6, no. 3, pp. 107–124, Sep. 2016, doi: 10.7441/joc.2016.03.07.

[2] R. Alami and R. Sergio, "Future-proofing strategies: Machine learning models for organizational resilience in emerging markets," in *Navigating the Technological Tide: The Evolution and Challenges of Business Model Innovation*, B. Alareeni and A. Hamdan, Eds., *Lect. Notes Netw. Syst.*, vol. 1083. Cham, Switzerland: Springer, 2024, pp. 487–501, doi: 10.1007/978-3-031-67431-0_47.

[3] S. Chakravarty and P. K. Dash, "A PSO based integrated functional link net and interval type-2 fuzzy logic system for predicting stock market indices," *Appl. Soft Comput.*, vol. 12, no. 2, pp. 931–941, 2012, doi: 10.1016/j.asoc.2011.09.013.

[4] M. Wuest, D. Weimer, C. Irgens, and K.-D. Thoben, "Machine learning in manufacturing: Advantages, challenges, and applications," *Prod. Manuf. Res.*, vol. 4, no. 1, pp. 23–45, 2016, doi: 10.1080/21693277.2016.1192517.

[5] S. Balaji, M. Patil, and C. McGregor, "A cloud based big data based online health analytics for rural NICUs and PICUs in India: Opportunities and challenges," in *Proc. IEEE 30th Int. Symp. Comput.-Based Med. Syst. (CBMS)*, Thessaloniki, Greece, 2017, pp. 385–390, doi: 10.1109/CBMS.2017.112.

[6] M. A. Boyacioglu and D. Avci, "An adaptive network-based fuzzy inference system (ANFIS) for the prediction of stock market return: The case of the Istanbul Stock Exchange," *Expert Syst. Appl.*, vol. 37, no. 12, pp. 7908–7912, 2010, doi: 10.1016/j.eswa.2010.04.045.

[7] A. Carvalhal and B. V. De Melo Mendes, "Evaluating the forecast accuracy of emerging market stock returns," *Emerg. Mark. Finance. Trade*, vol. 44, no. 1, pp. 21–40, 2008, doi: 10.2753/REE1540-496X440102.

[8] A. Abraham and B. Nath, "Hybrid intelligent systems for stock market analysis," in *Comput. Sci. ICCS 2001*, Berlin, Germany: Springer, 2001, pp. 657–665.

[9] J. G. Covin and D. P. Slevin, "Strategic management of small firms in hostile and benign environments," *Strateg. Manage. J.*, vol. 10, no. 1, pp. 75–87, 1989, doi: 10.1002/smj.4250100107.

[10] H. Chesbrough, "The logic of open innovation: Managing intellectual property," *Calif. Manage. Rev.*, vol. 45, no. 3, pp. 33–58, 2003, doi: 10.1177/000812560304500301.

[11] M. E. Porter, *Competitive Advantage: Creating and Sustaining Superior Performance*. New York, NY, USA: Free Press, 1985.

[12] G. T. Lumpkin and G. G. Dess, "Clarifying the entrepreneurial orientation construct and linking it to performance," *Acad. Manage. Rev.*, vol. 21, no. 1, pp. 135–172, 1996, doi: 10.2307/258632.

[13] J. B. Santos and L. A. L. Brito, "Toward a subjective measurement model for firm performance," *BAR Braz. Adm. Rev.*, vol. 9, no. SI, pp. 95–117, 2012, doi: 10.1590/S1807-76922012000500007.

[14] P. M. Thi Pham and B. T. Thi Dao, "A meta-analysis of risk taking and corporate performance," *Cogent Bus. Manage.*, vol. 9, no. 1, Art. no. 2064263, 2022, doi: 10.1080/23311975.2022.2064263.

[15] E. Moradi, S. M. Jafari, Z. M. Doorbash, and A. Mirzaei, "Impact of organizational inertia on business model innovation, open innovation and corporate performance," *Asia Pac. Manage. Rev.*, vol. 26, no. 4, pp. 171–179, 2021, doi: 10.1016/j.apmrv.2021.01.003.

[16] F. Moretti and D. Biancardi, "Inbound open innovation and firm performance," *J. Innov. Knowl.*, vol. 5, no. 1, pp. 1–19, 2020, doi: 10.1016/j.jik.2018.03.001.

[17] B. Bigliardi, G. Ferraro, S. Filippelli, and F. Galati, "The influence of open innovation on firm performance," *Int. J. Eng. Bus. Manag.*, vol. 12, Art. no. 184797902096954, 2020, doi: 10.1177/1847979020969545.

[18] H. Hilman and N. Kaliappen, "Do cost leadership strategy and process innovation influence the performance of Malaysia hotel industry?" *Asian Soc. Sci.*, vol. 10, no. 10, pp. 134–141, 2014, doi: 10.5539/ass.v10n10p134.

[19] A. H. G. Dutse and M. S. Aliyu, "Cost leadership, market orientation and business performance: An empirical investigation," *J. Qual. Meas. Anal.*, vol. 2, no. 2, pp. 28–42, 2018.

[20] R. Sancho-Zamora, I. Peña-García, S. Gutiérrez-Broncano, and F. Hernández-Perlines, "Moderating effect of proactivity on firm absorptive capacity and performance: Empirical evidence from Spanish firms," *Mathematics*, vol. 9, no. 17, Art. no. 2099, 2021, doi: 10.3390/math9172099.

[21] H. S. Bedi, "A contingency approach to proactiveness-business performance relationship," *Indian J. Mark.*, vol. 48, no. 12, pp. 34–45, 2018, doi: 10.17010/ijom/2018/v48/i12/139555.

[22] G. Andrevski and W. J. Ferrier, "Does it pay to compete aggressively? Contingent roles of internal and external resources," *J. Manage.*, vol. 45, no. 2, pp. 620–644, 2019, doi: 10.1177/0149206316673718.

[23] S. Nadkarni, T. Chen, and J. Chen, "The clock is ticking! Executive temporal depth, industry velocity, and competitive aggressiveness," *Strateg. Manage. J.*, vol. 37, no. 6, pp. 1132–1153, 2016, doi: 10.1002/smj.2376.

[24] T. L. Tufa, A. H. Belete, and A. A. Patel, "The autonomous side of EO and firm performance: The role of professional experience and entrepreneurial engagement," *Afr. J. Econ. Manag. Stud.*, vol. 12, no. 3, pp. 439–452, 2021, doi: 10.1108/AJEMS-09-2020-0445.

[25] E. Jang and Y. C. Kim, "Autonomy constrained: The dynamic interplay among job autonomy, work engagement, and innovative behavior under performance pressure," *Adm. Sci.*, vol. 15, no. 3, Art. no. 97, 2025, doi: 10.3390/admsci15030097.

[26] J. Bisbe and R. Malagueño, "Using strategic performance measurement systems for strategy formulation: Does it work in dynamic environments?" *Manag. Account. Res.*, vol. 23, no. 4, pp. 296–311, 2012, doi: 10.1016/j.mar.2012.05.002.

[27] R. Rajnoha, R. Štefko, M. Merková, and J. Dobrovič, "Business intelligence as a key information and knowledge tool for strategic business performance management," *Econ. Manag.*, vol. 19, no. 1, pp. 183–203, 2016.

[28] M. Kumar, "Dataset of relationship of entrepreneurship orientation, open innovation and cost leadership towards firm performance among small medium enterprise (SME's) in Malaysia," *Mendeley Data*, 2022, doi: 10.17632/FNJ7TSWXVG.2.

[29] I. Goodfellow, Y. Bengio, and A. Courville, *Deep Learning*. Cambridge, MA, USA: MIT Press, 2016.

[30] T. Hastie, R. Tibshirani, and J. Friedman, *The Elements of Statistical Learning: Data Mining, Inference, and Prediction*, 2nd ed. New York, NY, USA: Springer, 2009, doi: 10.1007/978-0-387-84858-7.

ISI Journal of Information Systems and Informatics
Published By Asosiasi Doktor Sistem Informasi Indonesia

[31] L. Breiman, "Random forests," *Mach. Learn.*, vol. 45, no. 1, pp. 5–32, 2001, doi: 10.1023/A:1010933404324.

[32] T. Chen and C. Guestrin, "XGBoost: A scalable tree boosting system," in *Proc. 22nd ACM SIGKDD Int. Conf. Knowl. Discov. Data Min.*, 2016, pp. 785–794, doi: 10.1145/2939672.2939785.

[33] S. S. Haykin, *Neural Networks and Learning Machines*, 3rd ed. New York, NY, USA: Prentice Hall, 2009.

[34] J. Kennedy and R. Eberhart, "Particle swarm optimization," in *Proc. IEEE Int. Conf. Neural Networks (ICNN)*, Perth, Australia, 1995, pp. 1942–1948, doi: 10.1109/ICNN.1995.488968.

[35] R. Storn and K. Price, "Differential evolution—A simple and efficient heuristic for global optimization over continuous spaces," *J. Global Optim.*, vol. 11, pp. 341–359, 1997, doi: 10.1023/A:1008202821328.

[36] K. P. Murphy, *Machine Learning: A Probabilistic Perspective*. Cambridge, MA, USA: MIT Press, 2012.

[37] C. M. Bishop, *Pattern Recognition and Machine Learning*. New York, NY, USA: Springer, 2006.

[38] J. Friedman, "Greedy function approximation: A gradient boosting machine," *Ann. Stat.*, vol. 29, no. 5, pp. 1189–1232, 2001, doi: 10.1214/aos/1013203451.