Sinkron : Jurnal dan Penelitian Teknik Informatika
Volume 9, Number 2, April 2025
DOI : https://doi.org/10.33395/sinkron.v9i2.14709

e-ISSN : 2541-2019
p-ISSN : 2541-044X

Loan Repayment Prediction Using XGBoost and Neural Network in Japan's Technical Internship Training

Mohammad Roffi Suhendry[1)*], Gerry Firmansyah[2)], Nenden Siti Fatonah[3)], Agung Mulyo Widodo[4)]
[1,2,3,4)]Universitas Esa Unggul, Indonesia
[1)]mohammad.roffi13@student.esaunggul.ac.id, [2)]gerry@esaunggul.ac.id, [3)]nenden.siti@esaunggul.ac.id,
[4)]agung.mulyo@esaunggul.ac.id

Submitted :April 19, 2025 | **Accepted** : April 24, 2025 | **Published** : April 26, 2025

Abstract: Delayed repayment of financial aid among participants in Japan's Technical Internship Training Program presents challenges for training institutions in managing funds efficiently. To address this issue, this study aims to compare the performance of two machine learning models: Extreme Gradient Boosting (XGBoost) and Multi-Layer Perceptron (MLP) in predicting the likelihood of delayed loan repayments. The research begins with data preprocessing, including handling missing values, normalization, and feature selection based on a correlation threshold of 0.06, where features with absolute correlation values below this threshold are excluded. Three models are tested: XGBoost Default, XGBoost optimized using GridSearchCV, and MLP. These models are evaluated using performance metrics such as accuracy, precision, recall, F1-score, and ROC-AUC. The XGBoost Default model achieves the highest accuracy at 95% and precision of 95%, although its recall is slightly lower at 83%. Tuning XGBoost improves recall to 84%, albeit with a marginal reduction in accuracy to 94%. In contrast, the MLP model demonstrates the lowest performance, with an accuracy of 92% and recall of 74%, indicating limitations in identifying delayed repayments. XGBoost also outperforms MLP in terms of ROC-AUC, scoring 91% compared to MLP's 86%. These findings suggest that XGBoost is the more effective model for this predictive task. The results have practical implications for training institutions, enabling better participant selection, reducing repayment delays, and supporting more effective financial aid management.

Keywords: Machine Learning; XGBoost; Multi-Layer Perceptron; Late Payment Prediction; Loan Repayment

INTRODUCTION

The Technical Internship Training Program (TITP) was officially launched in 1993 with the aim of transferring Japan's advanced skills and technologies to developing countries, including Indonesia. This program is expected to foster international cooperation through human resource development and support economic growth in participating countries (JITCO, n.d.) . Prior to departure, prospective trainees are required to complete technical and language training at a certified training institution (Lembaga Pelatihan Kerja/LPK). However, the obligation to bear educational and administrative costs often creates a significant financial burden. Many trainees struggle to fulfill these expenses, indicating the urgent need for a more accessible and flexible financing mechanism (Hermann & Fauskanger, 2024).

To address this issue, a private training institution introduced a loan assistance program to cover training fees, administrative costs, and travel expenses. The loan is repaid over a one-year period after trainees begin working in Japan (Guan, Suryanto, Mahidadia, Bain, & Compton, 2023). Despite this effort, delayed repayments remain a persistent problem. In 2022, 22% of trainees failed to meet their repayment deadlines, resulting in Rp 4.5 billion in outstanding loans. This not only disrupts the institution's cash flow but also limits its ability to support future participants, threatening the sustainability of the program (Koc, Ugur, & Kestel, 2023).

While loan assistance mechanisms have been implemented to ease the financial burden, the selection process for aid recipients continues to rely on subjective judgment rather than data-driven assessments (Fhadli & Hi Usman, 2023). Moreover, existing research has yet to fully explore the potential of predictive analytics particularly

*name of corresponding author

Sinkron : Jurnal dan Penelitian Teknik Informatika
Volume 9, Number 2, April 2025
DOI : https://doi.org/10.33395/sinkron.v9i2.14709
e-ISSN : 2541-2019
p-ISSN : 2541-044X

machine learning techniques, to identify trainees at risk of defaulting on their loans. This gap highlights the need for robust, systematic approaches that leverage historical data to enhance institutional decision-making and financial sustainability (Alzubaidi et al., 2021).

This study aims to develop a machine learning-based predictive model to identify potential repayment risks among prospective trainees. Through this approach, the institution can improve its participant selection process, minimize financial risks, and ensure the long-term continuity of the aid program. This research seeks to answer how predictive models particularly those using machine learning can serve as effective decision-support tools in the financial management of training institutions (Nurdin et al., 2023) .

This study contributes to both practical applications and academic literature. Practically, it proposes a predictive analytics approach using machine learning to improve the selection process for loan recipients in technical training programs, enabling institutions to mitigate repayment risks and ensure financial sustainability. Academically, the study addresses a notable gap by integrating machine learning techniques into the domain of financial risk assessment in international vocational training contexts. It advances the understanding of data-driven decision-making in education financing and provides a foundation for future research on AI applications in institutional risk management.

LITERATURE REVIEW

Several studies have investigated the use of machine learning models for credit risk classification, highlighting various optimization techniques and model performances. (Yulianti, Soesanto, & Sukmawaty, 2022) demonstrated that XGBoost achieved 80.02% accuracy in credit card classification, which improved to 83.42% after hyperparameter tuning, confirming that parameter optimization enhances model performance in detecting high-risk customers. Similarly, (Arram, Ayob, Albadr, Sulaiman, & Albashish, 2023) compared multiple models and found that MLP Neural Network performed best, achieving 91.6% accuracy with high recall, making it more effective for identifying default risks. However, while LightGBM attained the highest accuracy (94.4%), its lower recall made it less suitable for risk detection.

Meanwhile, (Rao, Liu, & Goh, 2023) focused on automotive credit risk and discovered that PSO-XGBoost outperformed other models, achieving 83.11% accuracy, 88.60% precision, and 76.14% recall, with an AUC-ROC of 0.90. The integration of PSO optimization and Smote-Tomek Link significantly improved accuracy and model stability, making it an ideal method for vehicle credit scoring. Additionally, (Li, Stasinakis, & Yeo, 2022) introduced a hybrid XGBoost-MLP model for credit risk assessment in digital supply chain finance, outperforming several traditional models, including Logistic Regression, KNN, Naïve Bayes, Decision Tree, Random Forest, and SVM. Their proposed model achieved 98.3% accuracy and an AUC of 0.994, proving to be the most effective method in detecting high-risk credit cases. The model's success is attributed to feature selection with XGBoost and the incorporation of digital supply chain features, enhancing its predictive capability.

Furthermore, (He et al., 2022) found that DNN-XGBoost demonstrated higher accuracy and stability in credit risk assessment, with AUC increasing by 8.6% and Type I error reduced by 54.2%. This model outperformed Logistic Regression, Random Forest, and SVM, proving to be an effective solution for banks and financial institutions in mitigating default risks.(Chang et al., 2024) also supported this by showing that XGBoost achieved the highest performance among several machine learning and deep learning models, reaching 99.4% accuracy and outperforming Neural Networks, Logistic Regression, AdaBoost, and LightGBM. Their findings reinforced the model's superior capability in identifying bad credit customers. Similarly, (Maulana & Hidayati, 2025) showed that XGBoost achieved 96% accuracy and excelled in identifying minority churn classes among credit card users, outperforming Random Forest in several key metrics. Their research proves the practical application of XGBoost in Indonesian banking scenarios for churn and risk prediction.

In addition, (Sharifi, Jain, Arab Poshtkohi, seyyedi, & Aghapour, 2021) proposed a hybrid model combining Artificial Neural Networks with an Improved Owl Search Algorithm (IOSA) and a C5 decision tree to predict credit risk. Their method achieved 96% accuracy, 0.885 precision, and 0.83 recall, surpassing traditional models such as Random Forest and Multilayer Perceptron (MLP). This study confirms the potential of optimized neural network architectures in delivering reliable risk assessments in real banking environments

Machine learning has become essential in credit risk assessment, enabling financial institutions to make more accurate predictions. Among various models, XGBoost and Neural Networks have proven highly effective, outperforming traditional methods like Logistic Regression, Random Forest, and SVM. These advanced models offer better feature selection, model stability, and predictive accuracy.

Studies show that XGBoost-MLP achieves 98.3% accuracy with an AUC of 0.994, leveraging XGBoost's feature selection and MLP's deep learning strengths. Similarly, DNN-XGBoost improves AUC by 8.6% and reduces Type I error by 54.2%, enhancing risk detection. PSO-XGBoost also improves recall and model stability, making it ideal for financial risk assessment.

*name of corresponding author

Sinkron : Jurnal dan Penelitian Teknik Informatika
Volume 9, Number 2, April 2025
DOI : https://doi.org/10.33395/sinkron.v9i2.14709
e-ISSN : 2541-2019
p-ISSN : 2541-044X

With growing demand for accurate and scalable credit evaluation models, hybrid approaches combining XGBoost and Neural Networks offer a powerful solution. This study explores their potential in optimizing credit risk prediction, ensuring higher accuracy and reliability.

Based on the reviewed literature, XGBoost and Multi-Layer Perceptron (MLP) were selected for this study due to their proven effectiveness in handling classification problems with structured tabular data. XGBoost, as an ensemble learning method, offers strong performance with limited hyperparameter tuning and is particularly robust against imbalanced datasets. Meanwhile, MLP represents a deep learning approach capable of modeling complex, non-linear patterns in data, which makes it valuable for comparison. The use of both models allows for a balanced evaluation between tree-based and neural network-based algorithms in the context of loan repayment prediction.

METHOD

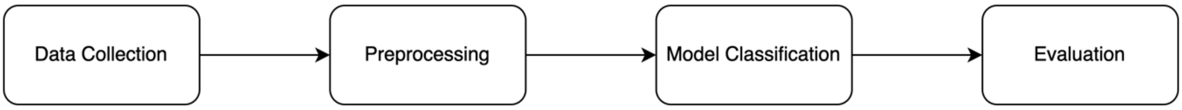

Fig 1. Research Methodology Flowchart

Data Collection

In the data collection stage, relevant financial and recruitment data are gathered to assess the repayment ability of participants in the technical internship training program in Japan. This study integrates financial transaction reports, recruitment information, and demographic details to identify the key factors that influence loan repayment.

Preprocessing

In the preprocessing stage, the collected data undergoes cleaning and preparation to ensure optimal use in the predictive model. This process is crucial to maintaining data quality, eliminating noise, and making it ready for further analysis.

Model Classification

Model classification is a key stage in data mining, where machine learning is used to analyze patterns and build predictive models. At this stage, processed data is used to train and test models to predict the repayment ability of technical internship training in Japan. The results help identify key factors influencing repayment and improve credit evaluation efficiency.

Evaluation

The evaluation stage measures the predictive model's performance using various metrics to ensure accuracy, stability, and real-world applicability. A well-evaluated model enhances the recruitment process for technical internship training in Japan by improving credit risk assessment and decision making.

RESULT

Data Collection

In the data collection stage, the data used in this study comes from financial reports and the recruitment process. During this stage, relevant information is systematically gathered to ensure the completeness and quality of the dataset. The collected dataset includes various key features that support further analysis, such as income level, financial transactions, recruitment status, demographic details, and work history. These features are selected based on their potential relevance to the assessment of repayment ability. Below is a list of features in the dataset, which will be utilized to extract insights and identify patterns in this research.

Table 1 Features of Dataset

#	Column	Total Data	Data Type
1	jenis_kelamin	1882	object
2	jumlah_keluarga	1878	float64
3	umur_saat_berangkat	1882	Int64
4	usaha	1881	object
5	ketrampilan	1882	object
6	total_hutang	1881	Float64
7	tgl_tahun_pertama	1882	Datetime64
8	tgl_bayar_terakhir	1855	Datetime64
9	total_pembayaran	1855	Float64
10	komitmen	1882	Int64
11	izin_keluarga	1882	Int64
12	pelatihan_prakeberangkatan	1882	Int64

*name of corresponding author

Sinkron : Jurnal dan Penelitian Teknik Informatika
Volume 9, Number 2, April 2025
DOI : https://doi.org/10.33395/sinkron.v9i2.14709
e-ISSN : 2541-2019
p-ISSN : 2541-044X

13	pekerjaan_dijepang	1882	Int64
14	kondisi_status_keluarga	1882	Int64
15	kesehatan	1882	Int64
16	sikap_kesopanan	1882	Int64
17	focus	1882	Int64
18	penilaian_keseluruhan	1880	Float64
19	hutang_pribadi	1882	Int64
20	hutang_orang_tua	1882	Int64
21	telat_bayar	1882	Int64
22	iq	1750	Float64

The table presents a summary of a dataset consisting of 22 columns with various data types. The dataset contains a total of 1,882 rows, though some columns have fewer entries, indicating missing data. In the predictive modeling process, the telat_bayar column serves as the primary target variable to be predicted.

Table 2. Total Record of Target

#	Column
0	1412
1	470

The image displays the data distribution in the 'telat_bayar' column, which serves as the target variable in the predictive model. The dataset consists of 1,412 entries labeled as 0, indicating on-time payments, and 470 entries labeled as 1, representing delayed payments.

Preprocessing

In the preprocessing stage, the researcher performs a thorough examination of the dataset to ensure data quality and consistency. One of the key activities in this stage is identifying and handling features that contain null values. This process involves checking for missing or incomplete data entries that could affect the accuracy and reliability of the predictive model. Depending on the nature and distribution of the missing values, appropriate strategies such as imputation or removal may be applied to prepare the data for the modeling phase. This step is essential to maintain the integrity of the dataset and to ensure optimal performance of the classification model.

Table 3. Display of Features with Null Values

#	Column	Total Null Values
1	jenis_kelamin	0
2	jumlah_keluarga	4
3	umur_saat_berangkat	0
4	usaha	1
5	ketrampilan	0
6	total_hutang	1
7	tgl_tahun_pertama	0
8	tgl_bayar_terakhir	27
9	total_pembayaran	27
10	komitmen	0
11	izin_keluarga	0
12	pelatihan_prakeberangkatan	0
13	pekerjaan_dijepang	0
14	kondisi_status_keluarga	0
15	kesehatan	0
16	sikap_kesopanan	0
17	focus	0

*name of corresponding author

Sinkron : Jurnal dan Penelitian Teknik Informatika
Volume 9, Number 2, April 2025
DOI : https://doi.org/10.33395/sinkron.v9i2.14709
e-ISSN : 2541-2019
p-ISSN : 2541-044X

18	penilaian_keseluruhan	2
19	hutang_pribadi	0
20	hutang_orang_tua	0
21	telat_bayar	0
22	iq	132

The missing values in the features jumlah_keluarga, total_piutang, and penilaian_keseluruhan are handled by filling them with the median to maintain data stability, especially when dealing with non-normal distributions or outliers. Meanwhile, the usaha feature is filled using the mode (most frequent value).

After handling missing values, categorical features in the dataset are processed using encoding techniques. Label Encoding is applied to convert categorical values into numerical representations for machine learning models. In this case, the features jenis_kelamin, usaha, and keterampilan are encoded.

Next, the researcher conducted feature engineering on the tgl_tahun_pertama and tgl_bayar_terakhir features to enhance data quality before modeling. Since both features are of the datetime type, a data transformation was applied to extract more relevant information. One of the steps taken was adding a new feature called selisih_hari_pembayaran, calculated by subtracting tgl_tahun_pertama from tgl_bayar_terakhir. This feature measures the time span between the last payment date and the initial date, providing deeper insights into payment delays or participant payment patterns. By incorporating this feature, the machine learning model can better recognize the relationship between payment timing and the likelihood of delays, thereby improving the accuracy of predicting repayment risks.

In addition, the target variable (telat_bayar) was found to be imbalanced, with approximately 75% of samples labeled as “on-time” and only 25% as “delayed”. This imbalance may lead to model bias toward the majority class. While XGBoost inherently handles imbalance to some extent via its scale_pos_weight parameter, additional resampling methods such as SMOTE (Synthetic Minority Oversampling Technique) or the use of class weighting could be considered in future research to further address this issue and improve the model’s sensitivity to minority class predictions.

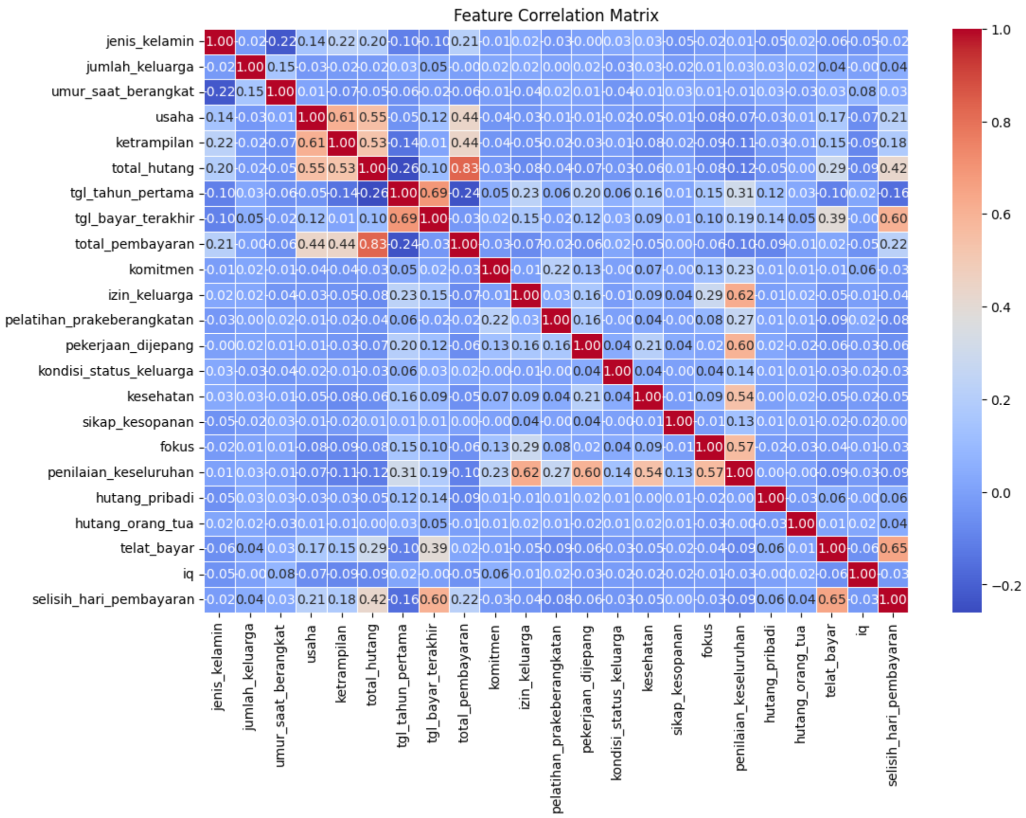

Fig 2. Feature Correlation Matrix

*name of corresponding author

Sinkron : Jurnal dan Penelitian Teknik Informatika
Volume 9, Number 2, April 2025
DOI : https://doi.org/10.33395/sinkron.v9i2.14709
e-ISSN : 2541-2019
p-ISSN : 2541-044X

Based on the feature correlation matrix above, two features, total_hutang and total_pembayaran, exhibit a very high correlation. To prevent redundancy and multicollinearity issues, one of these features must be removed from the dataset. High correlation between two features can lead to overfitting and reduce the interpretability of the model, making feature selection an essential step in data preprocessing.

Additionally, any feature with a correlation of 0.06 or lower with telat_bayar was removed. This threshold was determined based on empirical experimentation, where features with $|r| < 0.06$ consistently showed negligible impact on model performance during preliminary testing. Removing such weakly correlated features helps reduce dimensionality and noise, allowing the model to focus on more relevant predictors. This approach is in line with common practices in feature selection, where low-correlation variables are excluded to enhance computational efficiency and generalization capability.

By removing redundant and weakly correlated features, we can improve model efficiency, reduce dimensionality, and minimize noise that does not contribute significantly to predictive accuracy. This process ensures that the model focuses only on the most relevant features, ultimately leading to better generalization and more accurate predictions. If additional features are found to have very low or near-zero correlation, further feature selection should be considered to enhance the model's reliability and robustness.

Model Classification

After preprocessing, the next step is model classification. The dataset is split into 80% for training and 20% for testing to ensure proper evaluation of model performance. In this stage, the researcher develops and evaluates predictive models to assess the repayment ability of participants in the technical internship training program. Two machine learning algorithms are employed in this study: XGBoost Classifier and Multi-Layer Perceptron (MLP).

The process begins with the XGBoost model, which is trained using the training dataset and evaluated using default settings and optimized configurations via GridSearchCV. Performance metrics such as accuracy, precision, recall, F1-score, and ROC-AUC are calculated to assess the model's predictive capability.

To ensure comprehensive analysis, the XGBoost model is compared with a neural network approach using the MLP classifier. The MLP is constructed using two hidden layers with ReLU activation and a sigmoid output layer for binary classification. The model is compiled with the Adam optimizer and trained over 50 epochs. Predictions are then generated and evaluated using the same set of performance metrics.

This classification stage provides insight into the effectiveness of each algorithm in identifying key repayment patterns. By comparing results from both models, the study determines the most suitable approach for accurately predicting repayment ability.

Evaluation

Table 4. Comparation Results

Algorithm	Accuracy	Precision	Recall	F1-Score	ROC-AUC
XGBoost Default	95%	95%	83%	89%	91%
XGBoost with GridSearchCV	94%	93%	84%	88%	91%
MLP Neural Network	92%	93%	74%	83%	86%

The evaluation results indicate that XGBoost Default achieves the highest accuracy (95%), making it the most reliable model for overall predictions. However, XGBoost with GridSearchCV demonstrates higher recall (84%) compared to XGBoost Default (83%), meaning it is better at identifying delayed payments, even though its accuracy is slightly lower at 94%. On the other hand, the MLP Neural Network performs the worst, with an accuracy of 92% and a recall of only 74%, indicating that it frequently fails to detect delayed repayment cases. Additionally, ROC-AUC scores show that XGBoost (91%) outperforms MLP (86%), proving that XGBoost is more effective in distinguishing between on-time and delayed payments. Overall, XGBoost is the superior model for predicting repayment risks, and the GridSearchCV optimization enhances recall, making it a more balanced choice for financial risk assessment in loan assistance programs.

*name of corresponding author

Sinkron : Jurnal dan Penelitian Teknik Informatika
Volume 9, Number 2, April 2025
DOI : https://doi.org/10.33395/sinkron.v9i2.14709
e-ISSN : 2541-2019
p-ISSN : 2541-044X

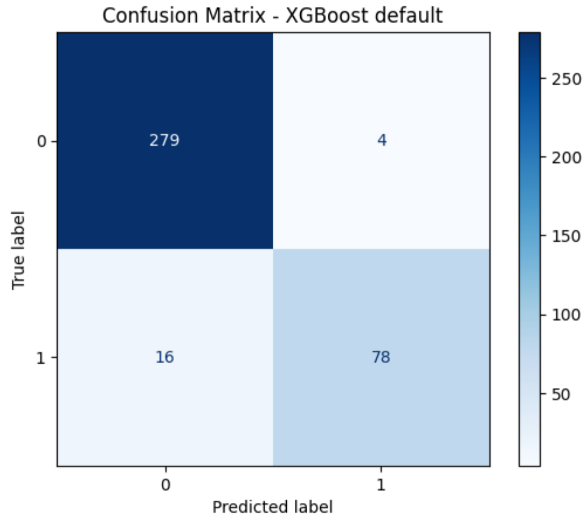

Fig 3. Confusion Matrix XGBoost Default

Following the classification modeling process, the subsequent step is model evaluation. The confusion matrix for the XGBoost Default model demonstrates its performance in a binary classification task, where it successfully classifies most cases with high accuracy (94.7%). The model correctly identifies 279 true negative cases (non-defaulters) and 78 true positive cases (delayed payments). However, it misclassifies 4 cases as false positives, incorrectly labeling non-defaulters as defaulters, and fails to detect 16 actual defaulters (false negatives). With a precision of 95.1%, the model is highly reliable when predicting delayed payments, as 95.1% of its positive predictions are correct. Meanwhile, its recall of 83% indicates that the model successfully identifies 83% of actual defaulters but misses the remaining 17%, suggesting a slight trade-off between precision and recall.

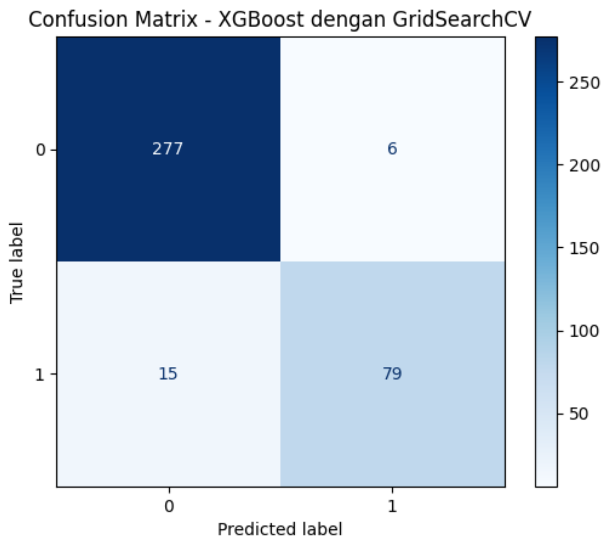

Fig 4. Confusion Matrix XGBoost With GridSearchCV

The confusion matrix for the XGBoost model optimized with GridSearchCV shows high accuracy in binary classification. The model correctly identifies 277 true negatives (TN) and 79 true positives (TP), while misclassifying 6 false positives (FP) and 15 false negatives (FN). Compared to the default XGBoost model, this version improves recall, enhancing its ability to detect delayed payments. However, the slight increase in false positives indicates a minor trade-off. Overall, the optimized model offers a better balance between precision and recall, making it more effective for predicting repayment risks.

*name of corresponding author

Sinkron : Jurnal dan Penelitian Teknik Informatika
Volume 9, Number 2, April 2025
DOI : https://doi.org/10.33395/sinkron.v9i2.14709
e-ISSN : 2541-2019
p-ISSN : 2541-044X

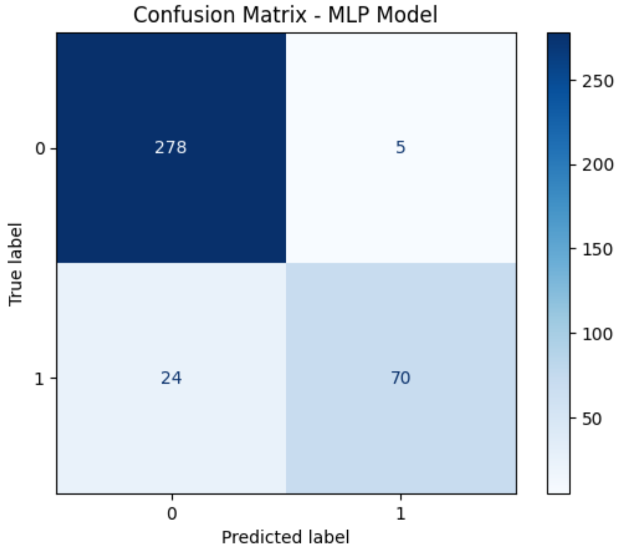

Fig 5. Confusion Matrix MLP

The confusion matrix for the MLP model shows that it correctly classifies 278 true negatives (TN) and 70 true positives (TP) but misclassifies 5 false positives (FP) and 24 false negatives (FN). Compared to XGBoost, MLP has lower recall, missing more delayed payments. While maintaining high accuracy, its weaker ability to detect repayment delays makes it less effective for financial risk assessment.

DISCUSSIONS

The findings of this study highlight the comparative strengths and limitations of XGBoost and Multi-Layer Perceptron (MLP) in predicting delayed loan repayments among participants in Japan's Technical Internship Training Program. The XGBoost Default model delivered the highest accuracy (95%) and precision (95%), indicating its robustness and reliability for overall prediction tasks. However, its recall score (83%) suggests a modest limitation in identifying all defaulters, implying that while it is precise, some cases of late payment may still be missed.

To enhance recall performance, the model was further optimized using GridSearchCV, which slightly reduced accuracy to 94% but improved recall to 84%. This demonstrates that hyperparameter tuning plays a critical role in adjusting model behavior to prioritize specific objectives in this case, better identifying potential repayment delays. The improved recall indicates a stronger capability to detect defaulters, which is crucial in financial risk management where under-detection can lead to substantial financial losses.

In contrast, the MLP model, despite achieving a relatively high accuracy (92%) and precision (93%), exhibited the lowest recall (74%). This suggests that while MLP is consistent in overall classifications, it lacks sensitivity in detecting late payments, making it less effective in real-world applications where identifying all potential risks is a priority. The lower ROC-AUC (86%) of MLP compared to XGBoost's 91% further supports the conclusion that XGBoost offers superior classification performance.

It is important to note that, unlike XGBoost, the MLP model was not subjected to hyperparameter tuning. This may have contributed to its relatively lower performance. Future studies are encouraged to apply grid or randomized search techniques for tuning MLP parameters such as the number of neurons, batch size, learning rate, and dropout rate. Doing so would allow a fairer performance comparison and reveal the model's true potential.

Moreover, in the context of financial risk prediction, false negatives cases where delayed repayments are misclassified as on-time can result in significant losses. Therefore, recall is often a more critical metric than accuracy. A model with slightly lower accuracy but higher recall may be more desirable in operational settings. Future work should consider using precision-recall curves or cost-sensitive evaluation strategies to better capture this trade-off and align predictions with institutional risk priorities.

Furthermore, the confusion matrix analysis reveals that both XGBoost models misclassified fewer instances than MLP. The optimized XGBoost model achieved a better balance between false positives and false negatives, offering a more dependable framework for supporting institutional decision-making regarding loan disbursement and risk profiling.

These results are consistent with prior studies (He et al., 2022; Li et al., 2022; Rao et al., 2023) that emphasize the strength of ensemble methods and the benefits of combining feature selection with model tuning. Additionally,

*name of corresponding author

Sinkron : Jurnal dan Penelitian Teknik Informatika
Volume 9, Number 2, April 2025
DOI : https://doi.org/10.33395/sinkron.v9i2.14709
e-ISSN : 2541-2019
p-ISSN : 2541-044X

the use of correlation-based feature filtering and engineered features such as payment gap days played a vital role in improving predictive accuracy.

CONCLUSION

Based on the results obtained, this study concludes that the XGBoost model, both in its default form and after optimization with GridSearchCV, demonstrates the best performance in predicting delayed loan repayments among participants in Japan's Technical Internship Training Program. The default XGBoost model achieved high accuracy and precision, while the optimized version showed better recall, making it more effective in identifying potential late repayments.

These findings indicate that XGBoost can serve as a reliable decision-support tool for financial risk management, especially in selecting qualified candidates for loan assistance programs. The model offers practical benefits for training institutions in minimizing the risk of delayed repayments and improving the overall efficiency of financial operations.

However, this study has limitations in terms of model interpretability and the range of tuning techniques applied. Future research is encouraged to explore time-based feature development, implement more advanced evaluation strategies, and integrate interpretability methods such as SHAP or LIME to enhance transparency and trust in model predictions.

With further improvements, the model developed in this study has strong potential to become a more accurate, adaptive, and applicable solution for real-world use, particularly in managing financial aid programs for outbound training participants.

REFERENCES

Alzubaidi, L., Zhang, J., Humaidi, A. J., Al-Dujaili, A., Duan, Y., Al-Shamma, O., … Farhan, L. (2021). Review of deep learning: concepts, CNN architectures, challenges, applications, future directions. *Journal of Big Data*, *8*(1). https://doi.org/10.1186/s40537-021-00444-8

Arram, A., Ayob, M., Albadr, M. A. A., Sulaiman, A., & Albashish, D. (2023). *Credit card score prediction using machine learning models: A new dataset*. Retrieved from http://arxiv.org/abs/2310.02956

Chang, V., Sivakulasingam, S., Wang, H., Wong, S. T., Ganatra, M. A., & Luo, J. (2024). Credit Risk Prediction Using Machine Learning and Deep Learning: A Study on Credit Card Customers. *Risks*, *12*(11). https://doi.org/10.3390/risks12110174

Fhadli, M., & Hi Usman, A. A. (2023). *Klasifikasi Kelayakan Pemberian Kredit Menggunakan Metode Decision Tree dengan Seleksi Fitur (Studi Kasus: PT. Adira Finance Cabang Kota Ternate)*.

Guan, C., Suryanto, H., Mahidadia, A., Bain, M., & Compton, P. (2023). Responsible Credit Risk Assessment with Machine Learning and Knowledge Acquisition. *Human-Centric Intelligent Systems*, *3*(3), 232–243. https://doi.org/10.1007/s44230-023-00035-1

He, X., Li, S., He, X. T., Wang, W., Zhang, X., & Wang, B. (2022). A Novel Ensemble Learning Model Combined XGBoost With Deep Neural Network for Credit Scoring. *Journal of Information Technology Research*, *15*(1), 1–18. https://doi.org/10.4018/jitr.299924

Hermann, R. R., & Fauskanger, E. A. (2024). Institutionalizing international internships in business education: an action research approach to overcoming barriers and driving systemic change in Norwegian business schools. *Scandinavian Journal of Educational Research*. https://doi.org/10.1080/00313831.2024.2369882

JITCO. (n.d.). What is the Technical Intern Training Program? Retrieved December 22, 2024, from https://www.jitco.or.jp website: https://www.jitco.or.jp/en/regulation/

Koc, O., Ugur, O., & Kestel, A. S. (2023). *The Impact of Feature Selection and Transformation on Machine Learning Methods in Determining the Credit Scoring*. Retrieved from http://arxiv.org/abs/2303.05427

Li, Y., Stasinakis, C., & Yeo, W. M. (2022). A Hybrid XGBoost-MLP Model for Credit Risk Assessment on Digital Supply Chain Finance. *Forecasting*, *4*(1), 184–207. https://doi.org/10.3390/forecast4010011

Maulana, B. A., & Hidayati, N. (2025). Churn Prediction in Credit Customers Using Random Forest and XGBoost Methods. *Indonesian Journal of Data and Science*, *6*(1), 82–90. https://doi.org/10.56705/ijodas.v6i1.215

Nurdin, A., Zunaidi, R. A., Arkan, M., Wicaksono, F., Lobita, A., & Martadinata, J. (2023). *ANALISIS KREDIT PEMBAYARAN BIAYA KULIAH DENGAN PENDEKATAN PEMBELAJARAN MESIN*. *10*(2), 271–280. https://doi.org/10.25126/jtiik.2023106301

Rao, C., Liu, Y., & Goh, M. (2023). Credit risk assessment mechanism of personal auto loan based on PSO-XGBoost Model. *Complex and Intelligent Systems*, *9*(2), 1391–1414. https://doi.org/10.1007/s40747-022-00854-y

Sharifi, P., Jain, V., Arab Poshtkohi, M., seyyedi, E., & Aghapour, V. (2021). Banks Credit Risk Prediction with Optimized ANN Based on Improved Owl Search Algorithm. *Mathematical Problems in Engineering*, *2021*. https://doi.org/10.1155/2021/8458501

*name of corresponding author

Sinkron : Jurnal dan Penelitian Teknik Informatika
Volume 9, Number 2, April 2025
DOI : https://doi.org/10.33395/sinkron.v9i2.14709
e-ISSN : 2541-2019
p-ISSN : 2541-044X

Yulianti, E. H., Soesanto, O., & Sukmawaty, Y. (2022). Penerapan Metode Extreme Gradient Boosting (XGBOOST) pada Klasifikasi Nasabah Kartu Kredit. *JOMTA Journal of Mathematics: Theory and Applications*, *4*(1).

*name of corresponding author