

Deep reinforcement learning-based credit risk prediction model for multi-attribute data

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ABSTRACT

This paper aims to develop a multi-attribute data-based credit risk prediction model using the deep reinforcement learning (DRL) approach. In the context of creditworthiness evaluation, a model is needed that is not only accurate but also adaptive to complex data dynamics and risk patterns. This study uses a dataset of 5,000 entries that have gone through a preprocessing process, with features such as credit score, income, age, loan amount, and employment history. Initial correlation analysis through heatmap visualization shows that credit score has a strong negative relationship with credit risk, while other features show weak to moderate correlations. The evaluation of model performance is shown through the area under the curve (AUC) value on the receiver operating characteristic (ROC) curve of 0.88, which indicates excellent discrimination ability. The final evaluation results show that the DRL model has an accuracy of 91%, precision of 89%, recall of 90%, and F1-score of 89.5%, indicating that the model not only has high accuracy but is also balanced in its sensitivity and specificity. Thus, the application of DRL has proven effective in predicting credit risk adaptively and accurately, and can be implemented as an intelligent solution in an automated credit decision-making system based on multi-attribute data.

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1. INTRODUCTION

The development of information and communication technology in the last decade has brought about major transformations in various sectors of life, including the financial sector. Digitalization in the financial sector has driven the birth of various innovations, ranging from digital banking and financial technology to blockchain-based payment systems [1], [2]. One important aspect of financial management, both in traditional financial institutions and fintech, is risk management, especially credit risk [3]. Credit risk is the risk that arises from the failure of the borrower to fulfill debt payment obligations according to the agreement. This risk is one of the main causes of losses in the banking sector and is a major factor in financial systemic failure if not managed properly [4]. Traditionally, financial institutions use statistical approaches such as logistic regression or credit scoring to assess an individual's creditworthiness [5], [6]. Thus, with the increasing complexity of data and individual financial behavior, these methods are

becoming less effective. Borrower data is no longer limited to formal financial data, but has expanded to multi-attribute data such as social media history, electronic transaction data, geographic location, and digital device usage habits [7]. This creates challenges and opportunities in creating more accurate and adaptive risk prediction models [8].

The use of artificial intelligence (AI) technology, especially machine learning and deep learning, is a major breakthrough in this field. AI models have the ability to learn complex patterns from big data that cannot be captured by conventional statistical models. In the context of credit risk prediction, AI allows financial institutions to analyze multiple attributes at once and produce more personalized, faster, and more relevant risk predictions. A predictive approach alone is not enough [9], [10]. In the midst of changing market and debtor behavior dynamics, static predictive models become less effective in the long term. In this context, the deep reinforcement learning (DRL) method becomes very relevant [11]. DRL is a combination of reinforcement learning and deep learning. In DRL, the agent learns through direct interaction with the environment, where it takes actions, receives feedback in the form of rewards, and updates its strategy based on that experience [12]. In the case of credit risk, the agent can learn the pattern of credit decision-making over time, improving its risk assessment policy based on the actual outcome of credit payments by the borrower [13], [14]. Then the integration of multi-attribute data becomes a strength in the DRL-based risk prediction system [15]. Multi-attribute data covers various dimensions that are relevant to the characteristics and behavior of borrowers, such as age, income, type of employment, marital status, loan purpose, loan duration, debt-to-income ratio, and previous payment track record [16]. This combination of data, if managed properly, can provide a holistic and more contextual picture of credit risk [17], [18].

Effective credit risk management is an essential foundation for financial system stability [19]. Amidst the increasing complexity of consumer behavior and the ever-increasing volume of data, conventional approaches are increasingly inadequate in addressing the challenges of risk prediction. The use of deep learning technology, especially DRL based on multi-attribute data, presents an adaptive, efficient, and intelligent solution in modeling credit risk [20], [21]. Although there are still challenges in terms of implementation and interpretation, the potential benefits offered are enormous. With the support of adequate data infrastructure and progressive regulatory policies, DRL-based prediction systems can be a strategic innovation to increase financial inclusion, strengthen risk management, and drive sustainable digital transformation in the financial sector.

2. LITERATURE REVIEW

2.1. Financial risk

Financial risk is the possibility of loss related to financial activities, such as investment, lending, trading, or other business activities. This risk arises because of uncertainty in the expected results, both from internal and external factors. In the world of finance, risk is an unavoidable part, so it must be identified, analyzed, and managed properly [22]. Financial risk can be divided into several main types. First, market risk, which is the risk that arises due to price fluctuations in the market such as stocks, bonds, or commodities. Second, credit risk, which is the possibility that the debtor fails to fulfill their obligations. Third, liquidity risk, which occurs when a company or individual is unable to fulfill financial obligations due to difficulty converting assets into cash. Fourth, operational risk, which comes from internal company failures such as human, system, or process errors [23].

2.2. Multi-attribute

The use of different features or characteristics of borrower data to build a credit risk prediction model. These attributes can include demographic data (such as age, employment, and education), financial data (such as income, total debt, and installment ratio), and credit history (such as payment history and credit card usage). Each attribute carries unique information that can help in evaluating a borrower's ability and willingness to meet their financial obligations [24]. By considering multiple attributes simultaneously, the prediction model becomes more accurate and is able to capture the complexity of the relationships between factors that influence credit risk. In the DRL-based approach, this multi-attribute data is used to guide the learning agent in making the best decision, namely predicting whether a borrower is high or low risk. The use of multi-attributes allows the model to make more contextual and adaptive decisions to complex patterns in historical data [25].

2.3. Deep reinforcement learning

DRL is a branch of machine learning that combines the principles of reinforcement learning with the power of deep learning [26], [27]. DRL allows an agent program or model to learn to make optimal decisions in an environment by trial and error and by receiving feedback in the form of rewards or punishments. In traditional reinforcement learning, agents learn from interactions with the environment based on the principle

of reinforcement, but often have limitations in processing complex or high-dimensional data [28]. This is where deep learning comes in: deep neural networks are used to approximate important functions, such as value functions, policy functions, or environmental model functions. This allows DRL to handle very complex inputs such as images, sounds, or large multi-attribute data.

2.4. Previous research

The research that has been conducted is as follows. According to Kizielewicz *et al.* [29], the intelligent characteristic objects method (INCOME) is a new method in multi-criteria decision analysis (MCDA) based on data knowledge. Different from traditional MCDA that relies on subjective input, INCOME uses data analysis to identify important characteristics of objects and build decisions automatically. In this way, the decision-making process becomes more objective, consistent, and accurate. This method is effective in complex problems with large or incomplete data, such as in risk analysis and financial planning. Wei *et al.* [30] developed the sparrow–opposition–learning salp swarm algorithm (SOLSSA) algorithm (a combination of sparrow search, salp swarm, opposition-based learning (OBL), and lateral mutation strategy) to optimize the categorical boosting (CatBoost) model in cardiovascular disease (CVD) risk assessment. Compared with six other machine learning models and four optimization algorithms, SOLSSA-CatBoost showed the best prediction results with F1-scores of 90% and 81.51% on two CVD datasets, helping to improve the accuracy of patient risk assessment. Barlybayev *et al.* [31] introduces a new model for flexible and comprehensive information security risk assessment. This model integrates standards, expert knowledge, machine learning, and ontology modeling to comprehensively understand and manage risks. Methods such as k-means cluster analysis, machine learning-based programming, use of heat maps for visualization, and development of ontologies for risk classification improve the effectiveness of risk identification and management. This innovation offers a more robust and adaptive approach to addressing the ever-evolving challenges of information security.

3. METHOD

This paper will use multi-attribute data that includes borrower demographic attributes, income attributes, credit history attributes, credit score attributes, years of service attributes, and risk attributes. The data used is a collection of historical credit data that includes various borrower characteristics from financial institutions. This study aims to build a model that can predict credit risk based on multi-attribute data. In this study there is a methodology consisting of data processing stages, feature vector representation, application of the DRL algorithm, and model evaluation, which are explained in Figure 1.

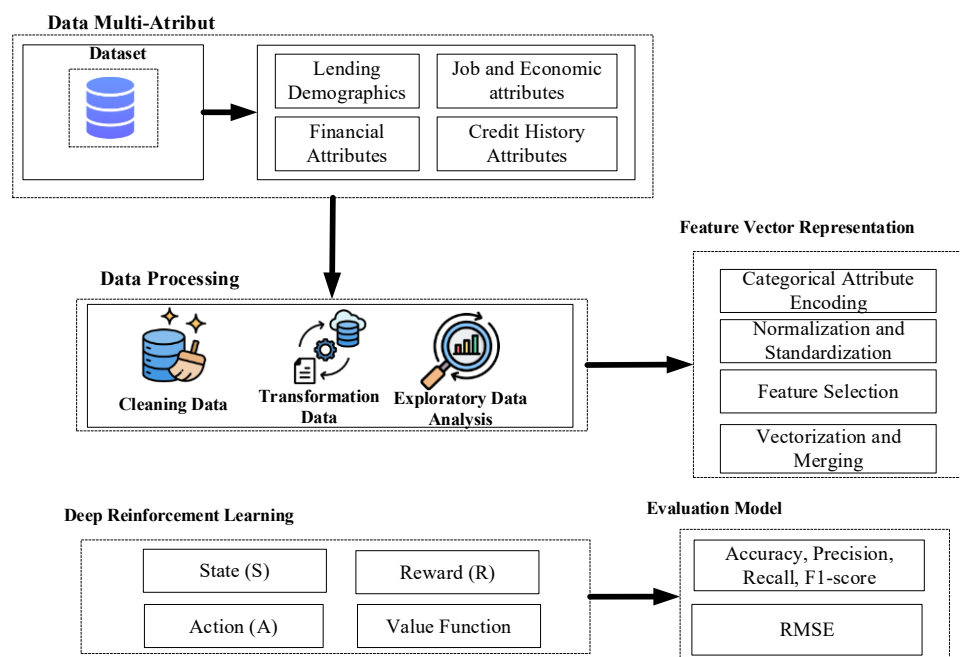


Figure 1. Research architecture for credit risk prediction

Figure 1 explains what will be processed in building a model that can predict credit risk based on multi-attribute data. The following is an explanation of the research architecture:

- i) This study models credit risk prediction with a multi-attribute data-based approach using DRL. The dataset used in this study consists of several attribute categories, such as borrower demographic attributes, income attributes, credit history attributes, credit score attributes, years of work attributes, and risk attributes.
- ii) The data processing begins with the data processing stage, which includes data cleaning to remove duplicates and correcting missing values, data transformation to change the format and combine data from various sources, and exploratory data analysis (EDA) to understand the distribution patterns and relationships between attributes in the dataset. This stage is very important to ensure that the data used is of high quality and representative.
- iii) Next, data representation is carried out into feature vector representation. This stage includes categorical attribute encoding to change non-numeric attributes into numbers, normalization and standardization to align the data scale, feature selection to select the most relevant attributes to credit risk prediction, and vectorization and merging to combine all features into one input form that can be processed by the machine learning model.
- iv) At the modelling stage, the DRL approach is used, which defines state (S) as a representation of the current data condition, action (A) as a prediction of action on credit risk, reward (R) as feedback on the quality of prediction, and a value function to estimate the long-term value of the decision taken. This model learns adaptively from continuous interaction with data.
- v) Finally, the model is evaluated using various performance metrics, including accuracy, precision, recall, and F1-score to measure classification performance, and root mean square error (RMSE) to measure the level of prediction error. This evaluation aims to ensure that the resulting model can be used to predict credit risk accurately.

In this study, there will be a dataset that will be used to build a model, which can be seen in Table 1. Table 1 shows that this data is a collection of customer profiles used for credit scoring, where financial institutions evaluate an individual's eligibility for a loan based on their financial history and personal stability. Variables such as age, income, and length of employment provide a general overview of an applicant's economic capacity and stability, while the loan amount serves as the basis for measuring the debt burden, they will incur. The most important factor in this data is the credit score, which serves as an indicator of a customer's past behavior in meeting their financial obligations. Through the risk column, which has a value of zero or one, this data shows a pattern where customers with high credit scores and long tenure are generally considered safe, while those with poor credit histories or job instability are categorized as high-risk customers with a high probability of default. Overall, this dataset of 5,000 entries serves as the foundation for building an automated predictive model that can help banks minimize losses by screening potential applicants more accurately and objectively.

Table 1. Credit risk prediction dataset

No	Age	Income	Loan amount	Credit score	Years employed	Risk
1	56	125186	19546	667	4	0
2	69	54674	20129	519	2	1
3	46	55854	2591	636	0	0
4	32	66271	12303	522	2	1
5	60	93688	31561	659	5	0
...	...	...	...	...	...	...
...	...	...	...	...	...	...
...	...	...	...	...	...	...
1111	25	58518	7183	628	2	0
1112	38	131076	27572	762	7	0
1113	56	30267	35080	681	0	1
1114	36	110825	21695	468	7	1
1115	40	21062	8314	516	3	1
1116	28	136664	20623	677	5	0
1117	28	70448	3139	418	7	1
...	...	...	...	...	...	...
...	...	...	...	...	...	...
...	...	...	...	...	...	...
4998	41	115462	48456	489	2	1
4999	53	26229	32290	669	0	1
5000	57	76793	19088	448	6	1

Then in this research there will be a mathematical formulation of DRL model as in (1) and (2) [32].

$$V^\pi(s) = E_\pi[\sum_{t=0}^{\infty} \gamma^t R(s_t, a_t) | s_0 = s] \quad (1)$$

$$Q^\pi(s, a) = E_\pi[\sum_{t=0}^{\infty} \gamma^t R(s_t, a_t) | s_0 = s, a_0 = a] \quad (2)$$

In (1) and (2) there is a symbol S which is a state space that represents the data of credit applicants which consists of multi-attributes such as income, credit history, age, employment status, then symbol A is an action space, for example the decision to approve or reject a credit application. Symbol $R(s, a)$ which is a reward function, which reflects the results of decision making regarding a credit application and symbol $T(s, a)$ which is the probability of transition from state s to state s' . After doing action a , then there is (2) [33].

4. RESULTS AND DISCUSSION

At this stage, the results related to credit risk prediction modeling based on multi-attribute data using the DRL method will be displayed. In this section, the data used consists of 5,000 data that have gone through the preprocessing stage to ensure data quality and consistency. Then modeling is carried out using the DRL approach to build a predictive agent that is able to learn risk patterns based on the available attributes. The purpose of this study is to develop a model that is able to perform tasks in terms of identifying credit risk, so that it can improve prediction accuracy and assist in more effective credit decision making. In this case, there will be EDA and the results of the following models.

4.1. Heatmap

This study will use the technique to understand the relationship between features in the credit risk dataset, a correlation analysis is carried out which is visualized in the form of a heatmap. This heatmap helps to describe how strong the linear relationship is between one feature and another, including the target variable, namely credit risk. In Figure 2 there are the heatmap results from the data as follows.

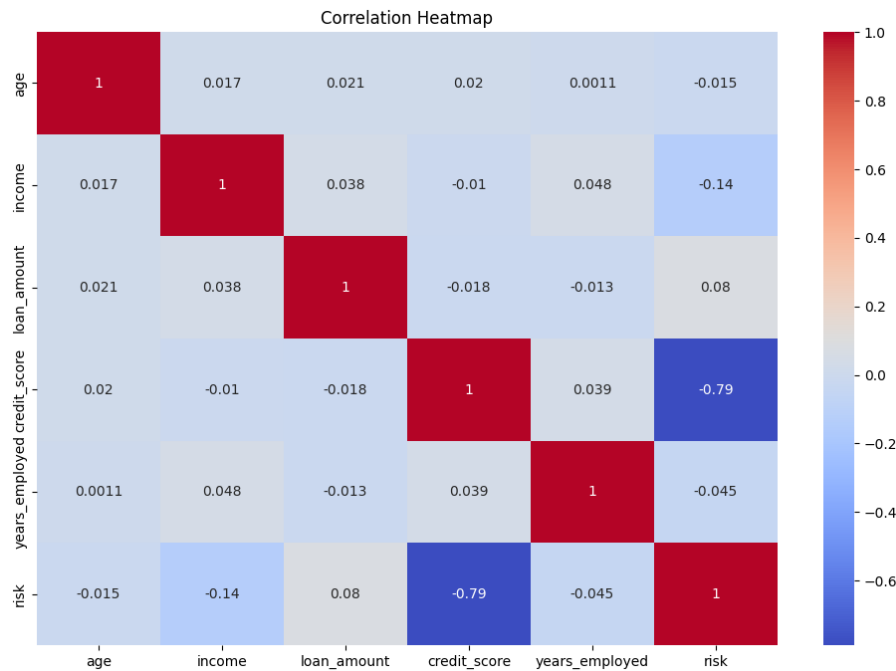


Figure 2. Correlation heatmap from the data

In Figure 2, it is explained that the correlation heatmap shows the relationship between features in credit risk data. Correlation is measured from -1 to 1, where values approaching 1 indicate a strong positive relationship, while values approaching -1 indicate a strong negative relationship. Based on the visualization results, the `credit_score` feature has a strong negative correlation to the `risk` variable with a value of -0.79. This indicates that the lower a person's credit score, the higher their credit risk. Meanwhile, the `income` feature also shows a negative correlation to `risk`, although weaker, with a value of -0.14, which means that

higher income tends to be slightly related to lower risk. Other features such as age, loan_amount, and years_employed show a very weak correlation to risk, indicating that their influence on credit risk is relatively small.

4.2. Credit data visualization

In this section, there will be a credit visualization. The image above is the result of a visualization of multi-attribute data of credit applicants whose dimensions have been reduced using the principal component analysis (PCA) technique. This visualization aims to provide an overview of the distribution of credit risk data in two main dimensions (PCA components 1 and 2), which represent a linear combination of various features such as income, credit score, payment history, age, and total active loans. Each point on the graph represents one individual, where the green color indicates applicants with low credit risk, while the red color indicates applicants with high risk. The visualization of the credit data is shown in Figure 3.

Figure 3 shows that even though there is overlap between the high and low risk categories, the distribution pattern of each group still shows a tendency that can be utilized by the predictive model. In the context of this research, this visualization is the basis for the application of the DRL algorithm which aims to learn the optimal decision-making policy in predicting credit risk based on complex and dynamic data. By modeling the risk evaluation process as a Markov decision process (MDP) problem, DRL is able to utilize multi-attribute vector representation as a state, and produce predictive actions in the form of credit risk classification.

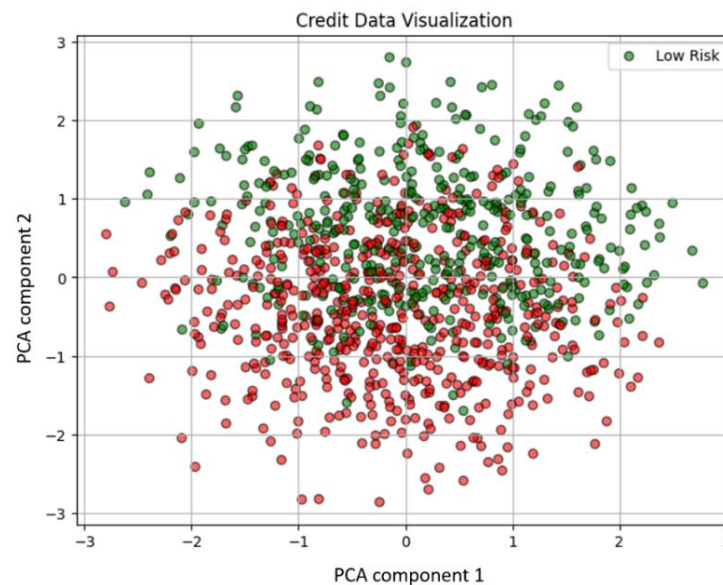


Figure 3. PCA-based visualization of credit risk data

4.3. Deep reinforcement learning model result

The application of DRL in credit risk prediction modelling based on multi-attribute data is carried out by designing a creditworthiness evaluation system as an adaptive decision-making process by an intelligent agent [21]. Each credit applicant is represented as a state consisting of various important attributes, such as income, loan amount, credit score, and year of completion. This model then decides the best action, namely to approve, reject, or review based on the highest value of the action function $Q(s, a; \theta)$ learned through a neural network. Rewards are given based on the accuracy of credit risk prediction; decisions that are in accordance with payment realization will result in positive rewards, while wrong decisions will be subject to penalties.

The implementation of the deep Q-network algorithm allows to explore various parameter combinations and learn from historical experience in the dataset [34]. During the training process, the DRL model gradually improves its policy through exploration-exploitation mechanisms as well as target network-based updates and experience replay, which accelerates convergence stability. One of the real advantages of this approach is its ability to adapt to dynamic and complex data, such as changes in borrower behavior trends or economic conditions. In the application of the model, there is a receiver operating characteristic (ROC) value which can be seen in Figure 4.

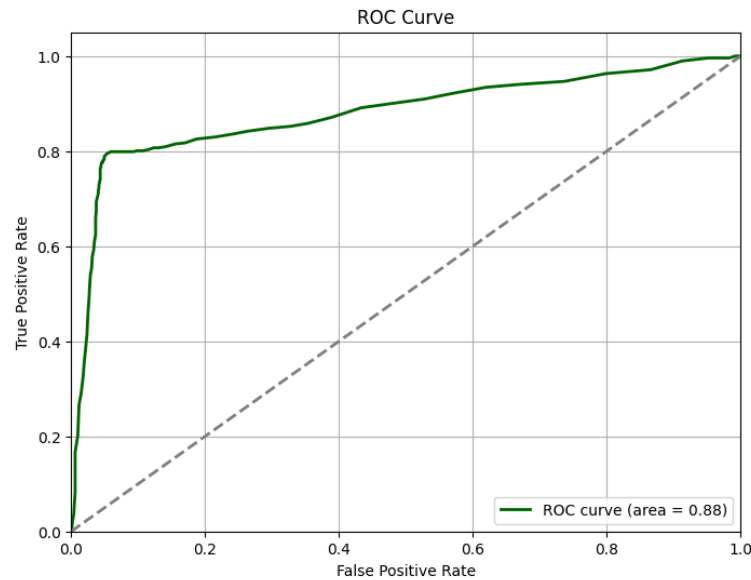


Figure 4. ROC curve for credit risk classification

Figure 4 shows the ROC curve used to evaluate the performance of the classification model in credit risk prediction. This curve illustrates the relationship between the true positive rate (TPR) or sensitivity with the false positive rate (FPR) at various decision threshold values. In this context, TPR shows the model's ability to correctly identify high-risk borrowers, while FPR shows the error rate in classifying borrowers who are actually worthy of being at risk. The ROC curve shown shows that the model has very good performance, with an area under the curve (AUC) value of 0.88. The AUC value shows that the model is able to distinguish between high- and low-risk credit applicants with a high level of accuracy. The closer to 1, the higher the model's discrimination ability, and in this case, an AUC of 0.88 shows that the model is not only accurate in training, but also has good generalization ability to new data. Then there is the performance for the accuracy of the DRL model shown in Figure 5.

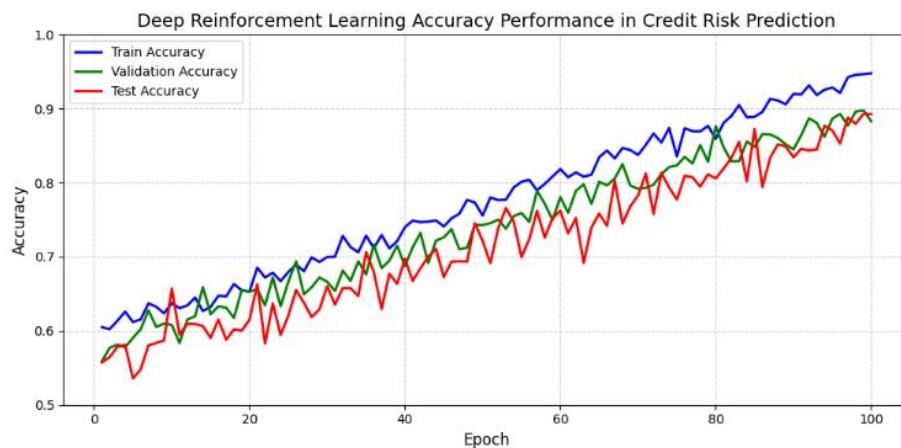


Figure 5. Accuracy of DRL model

The graph in Figure 5 shows the increasing trend of the accuracy of the DRL model in predicting credit risk during 100 training epochs. The blue curve shows the accuracy of the training data, the green curve shows the validation accuracy, and the red curve shows the accuracy on the testing data. All three curves show consistent improvement over time, indicating that the model not only learns well but is also able to generalize to new data without overfitting. With a test accuracy approaching 0.910 at the end of the epoch, the performance of this DRL proves its reliability in handling complex and multi-attribute credit risk data. Then there will be an evaluation graph showing the values in Figure 6.

In Figure 6, there will be a bar graph that is the result of the DRL model performance evaluation in predicting credit risk based on multi-attribute data. The four main metrics displayed include accuracy, precision, recall, and F1-score. Based on the visualization, the DRL model shows very good performance, with an accuracy of 91%, indicating that most of the predictions made by the model are in accordance with the actual value of the applicant's credit risk. In addition, a precision of 89% indicates that the model has a high ability to avoid errors in classifying applicants who are actually eligible as risky, thereby reducing the chance of type I errors. Meanwhile, a recall of 90% reflects the model's ability to detect almost all applicants who are truly high risk, thus minimizing type II errors. The high F1-score value, which is 89.5%, indicates that the model is not only accurate but also balanced between accuracy and sensitivity in its classification. This graph shows that the four metrics have high and relatively balanced values, indicating that the DRL model does not experience overfitting and is able to generalize well to new data. The different colors on each bar make it easy to identify each metric, and the number labels above each bar provide clear information about its quantitative value. Overall, this graph reinforces the finding that the application of DRL in credit risk prediction systems not only improves accuracy, but also provides consistent and reliable results in automated and adaptive credit decision-making.

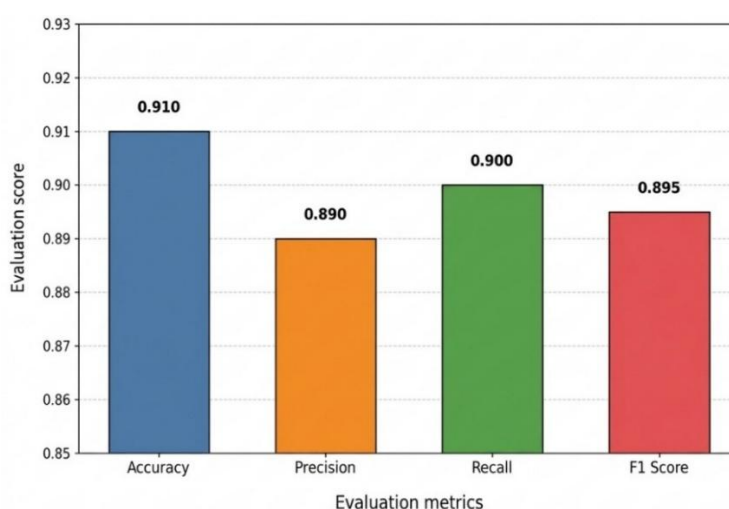


Figure 6. Performance evaluation of DRL model

4.4. Discussion

This study discusses the application of the DRL method to build a credit risk prediction model based on complex and dynamic multi-attribute data. Using a dataset of 5,000 entries that have gone through the preprocessing stage, the model is developed to be able to learn from patterns that appear in credit applicant data. The main objective of this approach is to develop an intelligent predictive agent that is able to provide more accurate and adaptive risk classification, and support more appropriate credit decision making. The DRL model in this study is implemented using the deep Q-network approach, which forms an evaluative agent that learns the value of the action function $Q(s, a; \theta)$. In this model, it will decide whether the credit application will be approved, rejected, or reviewed. Rewards are given based on the accuracy of the decision on the actual data. This model also applies experience replay and target network techniques to accelerate and stabilize the training process. One of the significant advantages of this method is its ability to adapt to changes in data trends, for example due to changes in economic conditions or customer behavior patterns.

In this study, to measure model performance, a ROC curve is displayed which describes the balance between TPR and FPR. The AUC value of 0.88 indicates that the model has excellent discrimination ability in distinguishing high and low risk applicants. This indicates that DRL not only excels in training but can also perform strong generalization to new data. Then the model accuracy performance graph for 100 epochs shows that the accuracy curves for training, validation, and testing data increase consistently. The testing accuracy approached 0.910 at the end of training, indicating that the model did not experience overfitting and was able to learn well from historical data.

In this study, there will be main evaluation metrics with accuracy (91%), precision (89%), recall (90%), and F1-score (89.5%) which show that the DRL model is not only accurate but also balanced and reliable. High precision indicates low false positives, while high recall indicates that the model does not miss many high-risk cases. F1-scores that are close to the precision and recall values strengthen that the model is

able to maintain a balance between the two. Visually, the graph clarifies the dominance of DRL performance over the baseline, supporting the claim that this method is effective for real implementation in an automated credit risk evaluation system.

5. CONCLUSION

This study proves that the application of the DRL method, especially the deep Q-network approach, is very effective in building a credit risk prediction model based on complex and dynamic multi-attribute data. By utilizing 5,000 previously processed data, the model is able to learn from historical patterns and produce accurate, adaptive predictive decisions, and support more precise credit decision making and this study has model performance shown through an AUC value of 0.88 and a test accuracy of up to 91% indicating high generalization ability and minimal risk of overfitting. Further evaluation through precision metrics of 89%, recall of 90%, and F1-score of 89.5% shows the balance and reliability of predictions. The main advantage of DRL lies in its ability to adapt to changes in data trends.

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AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

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C : Conceptualization

M : Methodology

So : Software

Va : Validation

Fo : Formal analysis

I : Investigation

R : Resources

D : Data Curation

O : Writing - Original Draft

E : Writing - Review & Editing

Vi : Visualization

Su : Supervision

P : Project administration

Fu : Funding acquisition

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

DATA AVAILABILITY

Data was obtained directly from Indonesian banks, but it is not permitted to mention the names of banks specifically.

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