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# CREDIT RISK POLICY 2019: IMPLEMENTATION OF MACHINE LEARNING FOR CREDIT RISK ASSESSMENT FOR MALAYSIAN CORPORATION

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**Abstract**: *The assessment of credit risk involves predicting loan default probability to evaluate risk. An incorrect decision poses potential risks to institutions. Advanced analytical tools are needed for more accurate predictive models. Researchers and practitioners focus on addressing these concerns. In 2019, Bank Negara Malaysia issued a Credit Risk policy urging the use of neural network models, such as machine learning and deep learning. This study evaluates the performance of these models for credit risk assessment using a dataset of Malaysian public listed corporations in three sectors: industrial products, consumer products, and construction. Four machine learning techniques (logistic regression, support vector machine, decision tree, and neural network), and three deep learning techniques (recurrent neural network, long short-term memory, and gated recurrent unit) were used. The support vector machine achieved the highest accuracy of 91.5% and 92.1% F1 score. This study demonstrates that machine learning can produce accurate results exceeding 90% accuracy and F1 score. Further improvements in machine learning and deep learning performance can be achieved through parameter manipulation and more data.*

**Keywords**: *Credit risk, deep learning, machine learning, and risk assessment*

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## Introduction

Credit risk is referred to the likelihood of facing a financial loss when a borrower is unable to repay a loan. To evaluate the borrower's capability to fulfill the agreed-upon debt obligations, financial institutions conduct credit risk assessments. Credit risk assessment involves evaluating the credit risk of a counterparty under the financial institution's credit acceptance standards (Credit Risk, 2019). There is a considerable demand for precise analytical prediction tools in the field of credit risk assessment, as they hold vital importance for all financial institutions. Consequently, this area of study has drawn the attention of numerous practitioners and researchers, who are actively engaged in exploring these matters (Halim et al., 2021).

Machine learning is a common term in the era of artificial intelligence (AI). Machine learning is the algorithm that can train a model based on the previous data to learn the pattern. Then, the model is used to predict the new data (Duarte & Barboza, 2020). In research in credit risk assessment, many studies have applied machine learning such as Abdullah (2021), Chen & Han (2021), Guerra et al. (2022), and Zhu et al. (2021). The common machine learning techniques used by these researchers are logistic regressions (LRs), neural networks (NNs), support vector machines (SVMs), and decision trees (DTs).

Currently, deep learning is the latest algorithm in machine learning, which is growing in popularity, and has been used in many domains such as in the financial area (Chen & Han, 2021), big data analytics (Fonseca & Cabral, 2017), and medical domain (Maier et al., 2019). Deep learning simulates the human brain's neural signals to the neural network algorithm (Exastax, 2018).

In 2019, Bank Negara Malaysia issued a Credit Risk policy, which is a guideline document for all financial institutions in Malaysia to perform comprehensive credit risk management including assessment, measurement, monitoring, and default management. The main purpose of the policy is stated as follows: "To ensure that credit risk management practices of financial institutions remain effective moving forward, amid the increased size and diversity of product offerings by financial institutions, greater internationalization of the financial system, as well as the growing role of domestic capital markets" (Credit Risk, 2019).

The credit risk policy dictates that a financial institution must establish a robust and comprehensive credit risk methodology with a particular focus on credit risk assessments. Financial institutions have advised the utilization of statistically driven methodologies, such as neural network models, which leverage historical data and can be assessed using accuracy measurements. This approach aims to establish an analytical framework supported by substantial empirical evidence (Credit Risk, 2019).

Based on the above statements, this study found that the policy is urging the use of neural network models, such as machine learning and deep learning, for credit risk measurement. As found by Halim, (2023), in Malaysia, the credit risk assessment study that applied machine learning is not yet widespread, which might be the factor of the lack of expertise in machine learning for the credit risk assessment domain. Therefore, this study aims to employ and measure the performance the machine learning and deep learning techniques for credit risk assessment. This study is only focusing on the credit risk assessment using Malaysian public listed corporations. This article is arranged as the following: Section 2 reviews the machine learning techniques for the credit risk assessment; Section 3 the research methodology used for this study; Section 4 the results and discussions; and Section 5 is the conclusion of this study.

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### Machine Learning Techniques for Credit Risk Assessment

Many studies have used machine learning techniques for credit risk assessment. The most used machine learning techniques for credit risk assessment studies are logistic regression (Guerra et al., 2022; Kwon et al., 2017; Vidhikhanduja & Juneja, 2020; Zhu et al., 2021), support vector machine (Abdullah, 2021; Guerra et al., 2022; Vidhikhanduja & Juneja, 2020; Zhang et al., 2021; Zhu et al., 2021), decision tree (Guerra et al., 2022; Halim et al., 2021; Zhu et al., 2021), and neural network (Abdullah, 2021; Kwon et al., 2017; Zhu et al., 2021). Deep learning is the most recent algorithm in the field of machine learning. Recently, many studies have employed deep learning as the technique for credit risk assessment study, such as recurrent neural networks (Kwon et al., 2017), long short-term memory networks (Chen & Han, 2021), and gated recurrent units (Halim et al., 2021).

As per the studies mentioned above, the best accuracy achieved by machine learning techniques is almost 80% and above. For example, Abdullah (2021) has achieved 88% accuracy using a neural network. The study has compared the performance of the machine learning techniques, including neural network, support vector machine, and Z-score. Z-score is the most common statistical technique used for credit risk assessment studies (Halim, 2023). In other instances, Vidhikhanduja & Juneja (2020) have found that logistic regression has outperformed the other techniques with 89% accuracy against the other machine learning techniques. As for the performance of deep learning techniques, Kwon et al. (2017) show that recurrent neural networks achieved the highest accuracy with 82.8%. Meanwhile, the findings by Halim (2023), gated recurrent units have outperformed others with 93% accuracy.

Based on the above findings, this study is implementing four machine learning techniques (logistic regression, support vector machine, decision tree, and neural network), and three deep learning techniques (recurrent neural network, long short-term memory network, and gated recurrent unit) for the credit risk assessment study. The following are the descriptions of the machine learning techniques used for this study.

### Logistic Regression

Logistic Regression (LR) introduced was introduced by Ohlson in 1980 and is aimed to solve the weakness of discriminant analysis on normality and equal covariances (Gepp & Kumar, 2015). LR uses categorical nominal and non-metric as the dependent variable; meanwhile, the metric variables are the independent variables (Fawzi et al., 2015). LR is commonly used for binary classification. LR computes coefficients $a$ and $b$ to minimize the discrepancy between actual and predicted values. The Naive Bayes method is employed to determine the likelihood of an event happening given another event that has occurred previously. The equation used for logistic regression is shown in equation (1), where $a$ is the probability that the hypothesis is true without prior knowledge about $b$ (Vidhikhanduja & Juneja, 2020).

$$P(a / b) = (P(b / a) \cdot P(a)) / P(b) \tag{1}$$

### Support Vector Machine

Support Vector Machine (SVM) was proposed in 1995 to comprise a class based on statistical learning techniques (Vapnik, 1999). SVM is employed to identify the hyperplane with the maximum margin that separates two classes. Each class is represented by points on a plot, and the classification outcome is determined by the class to which each point belongs. The support vectors, being the nearest points to the optimal hyperplane, play a crucial role in this process. (Belavagi & Muniyal, 2016). The optimal hyperplane was obtained based on the equal distance

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between two support vector lines, denominated as $\hat{r}$. $\hat{r}$ is defined as in equation (2). Figure 1 shows the support vector classification diagram.

$$\hat{r} = y(w^T x + b) = yf(x) \quad (2)$$

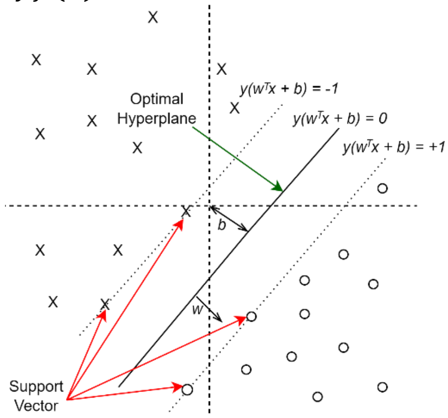


**Figure 1: Support Vector Classification Diagram**

Usually, data are not always linearly separable. The kernel function is required to identify the optimal hyperplane, by transforming the nonlinear data to separated data. The data is transformed into a new feature space through the kernel function, enabling the problem to be classified effectively. Among the frequently utilized kernel functions are linear, radial basis, polynomial, and sigmoid kernels (Zhang et al., 2021).

### Decision Tree

A Decision tree (DT) is a hierarchical tree structure that repeatedly divides data to create leaf nodes. These leaves are determined by a specific criterion and represent distinct classes. The resulting structure can be employed as a classifier. The DT structure consists of non-leaf representing attributes, and leaf nodes as class variables (Chou, 2019). DT utilizes information gain to split nodes, and the Gini index serves as a measure to determine node separation. The formula of the Gini index is shown in equation (3), where $J$ is the number of states and $\hat{p}_{mj}$ is the proportion of state $j$ in the $m$ region (Kim et al., 2020).

$$G = \sum_{j=1}^{j} \hat{p}_{mj} (1 - \hat{p}_{mj}) \quad (3)$$

### Neural Networks

According to Haykin (1999), Neural Networks (NN) are information-processing units inspired by the analytical processing of the human brain, achieved through interconnected neurons to solve problems. These networks learn from past experiences or data, enabling them to generate new information for decision-making. A typical NN model is the multilayer perceptron (MLP), which consists of three layers: input, hidden, and output. The input layer contains feature value nodes, while the output layer includes nodes for classification. NNs are highly versatile, capable of handling data with varying levels of complexity. However, the drawback is hard in explaining the causal relationships among variables (Le & Viviani, 2017).

### Recurrent Neural Network

Recurrent Neural Network (RNN) is built upon the principles of a neural network algorithm. Like a basic neural network, inputs are computed using nodes and activation functions, and the weights are adjusted to determine the optimal values. This calculation process is performed

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once for all nodes. However, due to its cyclic structure, RNN gains the advantage of an active function, wherein nodes are connected circularly to themselves, allowing it to effectively process sequential data (Kwon et al., 2017). Figure 2 shows the cyclic structure and its equivalent to a chain structure, where $X_t$ is the input, $Y_t$ is the output at the current step, *t*, and cyclic cell, *A* represents an algorithm that can be as simple RNN, Long Short-Term Memory (LSTM), or Gated Recurrent Unit (GRU).

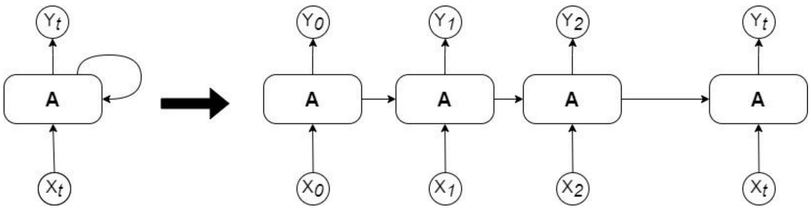


**Figure 2: Cyclic Structure of RNN**

### Long Short-Term Memory

Long Short-Term Memory (LSTM) solves the issue of vanishing gradients, which leads to zero slopes in RNN. LSTM is a weighted architecture that facilitates the effective transmission of gradients during back-propagation. It consists of units containing cells with multiple gates, enabling them to store, retrieve, and maintain cell information. This characteristic effectively addresses the problem of gradient disappearance observed in regular RNNs, allowing the RNN to retain and remember information over extended periods (Kwon et al., 2017). An LSTM unit consists of several components: an input gate, the cell state, a forget gate, and an output gate. These gates play crucial roles in controlling the flow of information into and out of the cell. The forget gate determines which information to discard, the input gate is responsible for updating the cell's state, and the output gate decides what information should be retained and carried forward (Dutta et al., 2020).

### Gated Recurrent Unit

Cho et al. (2014) introduced a novel recurrent unit called the gated recurrent unit (GRU), which enables the adaptive capture of dependencies across different time scales. Like LSTM, GRU also incorporates gate units to control the information flow within the unit, contained within the same memory cell. A GRU unit comprises an update gate, a reset gate, and the current memory content. These gates enable the GRU unit to store information in memory for a specific duration and subsequently transfer it to the current state, which can be further updated. The update gate determines whether the hidden state should be replaced with a new hidden state, while the reset gate decides whether to disregard the previous hidden state (Cho et al., 2014).

## Methodology

This study will use a dataset of Malaysian public listed corporations to compare the performance of the machine learning techniques for credit risk assessment based on three sectors: industrial products, consumer products, and construction. The data collection is focused on companies declared as PN17, which is a designation given by Bursa Malaysia to public listed companies facing financial difficulties (Halim, 2023). To perform the balance analysis, this study used 98 companies' profiles that declared PN17 as the negative sample and 98 for non-PN17 as the positive samples according to similar sectors, closest assets, and the same status year.

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Credit risk assessment relies on the financial indicators that depict the status of companies. These financial indicators are derived from the balance sheet and financial statement of each company, which, in turn, generate the necessary financial ratios. The financial ratios serve as essential features utilized in the credit risk assessment study. Table 1 shows the financial ratio used in this study.

Seven models were created in this study based on the machine learning techniques described in Section 2, with each model corresponding to a specific machine learning technique. The development of these models followed the standard machine learning model development pipeline illustrated in Figure 3. This pipeline includes stages such as data collection, data extraction, and data pre-processing, which involve transforming raw data into clean data. Once the data is pre-processed, it is ready to be used with machine learning techniques. To assess the model's performance, the cleaned data was split into a 70% training set and a 30% test set. The training set was employed to train the model, and the fitted model was then evaluated using the test set. Hyperparameter tuning, a crucial step in the model development pipeline, was performed to identify the optimal combination of parameters that would result in improved model performance during training.

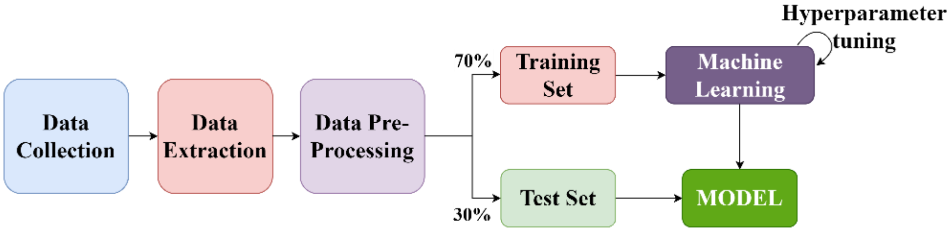


**Figure 3: Machine Learning Model's Development Pipeline**

**Table 1: The Financial Ratio used in this Study**

| **Financial Ratio** | **Description** |
|---|---|
| Gross Margin | Compares the gross margin to the net sales |
| Operating Margin | Measures the percentage of total revenues made up by operating income. |
| Net Margin | Measures the percentage of each dollar a business earns as profit at the end of the year |
| Asset Turnover | Measures a company's ability to generate sales from its assets by comparing net sales with average total assets |
| Return on Equity | Measures a company's ability to generate sales from its assets by comparing net sales with average total assets |
| Earnings Retention | Percentage of profits the company retains as retained earnings. The retention ratio refers to the proportion of net profits retained for corporate expansion rather than distributed as dividends |
| Quick Ratio | Measures the ability of a company to pay its current liabilities when they come due with only quick assets. |
| Current Ratio | Measures a firm's ability to pay off its short-term liabilities with its current assets |
| Asset-to-Equity | Measures the company's total assets to the amount owned by its shareholders and is an indicator of its level of debt |
| Debt-to-Equity | Measures the financial liquidity ratio that compares a company's total debt to total equity |

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In this study, the performance of all machine learning models is evaluated based on two metrics: accuracy and F1 score. These performance metrics are computed using a confusion matrix, which facilitates a comparison between the model's predicted classifications and the actual classifications, as illustrated in Figure 4. Accuracy represents the rate at which the model's predictions are correct over the entire dataset. On the other hand, the F1 score is a metric used to measure the harmonic mean between misclassified samples involving type I errors and type II errors. Type I errors occur when negative samples are incorrectly classified as positive samples, while type II errors occur when positive samples are incorrectly classified as negative samples. The equations for calculating accuracy and F1 scores are presented in equations (4) and (5) respectively.

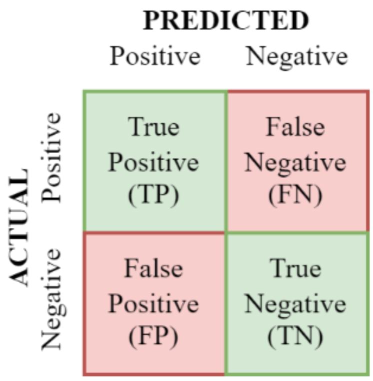


**Figure 4: Confusion Matrix**

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \tag{4}$$

$$\text{F1 Score} = \frac{TP}{TP + 0.5(FP + FN)} \tag{5}$$

**Results & Discussion**

Table 2 presents the accuracy and F1 score results for all the models developed. Overall, impressive performance was observed, with all models achieving a percentage of over 80% for both accuracy and F1 score. Among them, LR and SVM models stood out with the highest accuracy of 91.5%. However, SVM outperformed the LR model by achieving the best F1 score of 92.1%. On the other hand, the DT model demonstrated the lowest accuracy and F1 score.

The study's findings indicate that the SVM model performed exceptionally well, possibly due to the SVM's computation complexity being dependent on the number of support vectors found rather than the sample size's dimension. This characteristic allows SVM to maintain its performance even when dealing with small sample sizes, as it focuses on finding optimal margins of hyperplanes based on the support vectors determined by the algorithm. Additionally, the accuracy of the SVM model in this study surpassed Zhang et al. (2021) findings.

**Table 2: Accuracy and F1 Score of All Developed Models**

| Models | Accuracy (%) | F1 score (%) |
|---|---|---|
| LR | 91.5 | 91.8 |
| SVM | *91.5* | *92.1* |
| DT | 81.4 | 81.4 |

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| Models | Accuracy (%) | F1 score (%) |
|---|---|---|
| NN | 88.1 | 88.5 |
| RNN | 86.4 | 86.7 |
| LSTM | 89.8 | 90.3 |
| GRU | 88.1 | 88.5 |

Previous studies that reported the best performance by the DT model may be attributed to the utilization of ensemble or hybrid approaches, as discovered by Chou (2019). However, the DT model demonstrated the lowest performance in this study. The reason for this disparity is that the current study did not explore or incorporate hybrid or ensemble techniques, which were not the focus of the research. Based on these observations, it is concluded that the DT model might be weak when not supplemented with ensemble or hybrid methods.

Conversely, the neural network models, encompassing deep learning models such as NN, RNN, LSTM, and GRU, consistently generated comparable results, ranging from 86.4% to 89.8% for accuracy and 86.7% to 90.3% for F1 score. This similarity in outcomes can be attributed to the nearly identical structure shared by all these models, comprising input, hidden, and output layers. To enhance the performance of the deep learning models, the study should focus on robust parameter manipulation and the inclusion of additional data.

## Conclusion

The primary objective of this study is to assess and compare the performance of machine learning and deep learning techniques for credit risk assessment. The motivation behind this research stems from Bank Negara Malaysia's recommendation to adopt machine learning or deep learning techniques in credit risk policies. After conducting a comprehensive investigation, this study revealed that all the machine learning models achieved accuracy and F1 score exceeding 80%. Notably, the support vector machine model outperformed the others, attaining an accuracy of 91.5% and an F1 score of 92.1%.

This study emphasizes the importance of encouraging practitioners and researchers, particularly in Malaysia, to actively engage with machine learning for credit risk assessment. Despite the potential benefits, this research area has not yet gained widespread popularity, primarily due to a lack of expertise in this domain. For future studies, it is recommended to establish a comprehensive machine learning model development framework that incorporates various parameter-tuning techniques for each model. This approach will enhance the robustness of the models.

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