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Financial distress prediction for batik small and medium enterprises credit financing based on deep learning algorithm

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ABSTRACT

One of the biggest obstacles that any finance provider has when evaluating a borrower's creditworthiness is the prediction of financial trouble. The credit decision-making process is made more difficult for small and medium enterprises (SMEs) due to their inherent ambiguity, which raises financing costs and lowers the chance of approval. In order to estimate a binomial classifier for predicting financial hardship using logistic regression (LR), extreme gradient boosting (XGBoost), and artificial neural network (ANN) techniques, this study examines data from batik SMEs in Pekalongan city. Financial ratios predict the first period and grow in a multi-period model based on temporal factors, credit history, and age. Financial distress is defined as a substantial obstacle to a business's capacity to pay its debts as opposed to the potential for bankruptcy. The long short-term memory (LSTM) algorithm with more variables yields the best prediction accuracy. The study's conclusion indicates that in order to guarantee the accuracy of financial distress prediction, the time at risk must be adjusted.

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1. INTRODUCTION

Credit risk modelling begins with lenders who must calculate the capital requirements to support the loans provided. One of the efforts implemented is by requiring a minimum model as one of the requirements in bank asset allocation. Lenders can choose one of the credit risk management approaches, namely the standard approach or the internal rating-based approach [1]. This is what causes small and medium enterprises (SMEs) to receive different treatment from other business entities regarding credit risk. SMEs are one of the backbones of the world economy and the welfare of the country. One of the challenges faced by SMEs in recent decades is access to financing. In addition, capital availability requirements also put pressure on banks to provide loans to SMEs. The inability of banks to fund SMEs is hampered by the increasing burden that comes with increasing minimum capital ratios (which currently average 6% to 8%) [2]. Many studies have shown the importance of SMEs' health [3]–[6] in providing credit.

Edmister [7] effectively modelled basic credit evaluation for business organizations, and so pioneered credit risk modelling for SMEs. In the meantime, Altman and Sabato [8] looked at the theoretical and practical evaluation of SMEs' default likelihood. The developed model was able to predict financial difficulties for SMEs, resulting in a reduction in model requirements by 0.5%. Based on this, it can be said that: i) SMEs are different from large companies based on credit risk; and ii) Banks must differentiate the procedures for ranking and assessing SMEs in providing credit.

Credit to SMEs is positively impacted by the adoption of government guarantee programs, credit protection plans, and accounting standards [5]. Zhu *et al*. [6] stated that SME loans have a greater risk than large corporate loans. Thus, predicting financial distress is a key issue for lenders, both in determining the financial capacity of borrowers and when determining the capital requirements set by financial regulators. The main goal of bankruptcy prediction is to forecast when a corporation will cease to be viable; financial difficulty is more likely to be predicted when a company is having trouble fulfilling its responsibilities [2]. Sometimes financial hardship is merely a setback that passes quickly, but other times it results in bankruptcy. Lenders look at the time of creditworthiness assessment to identify the borrower's ability to repay their credit.

Research on credit risk modelling has expanded dramatically during the past 50 years, particularly in the works of Altman [9] and Merton [10]. Research has employed machine learning techniques to estimate credit risk and financial distress in the past 20 years, mainly abandoning classical modelling [8], [11]–[13]. Atiya [14] developed the first machine learning technique for financial crisis prediction by simulating traditional predictions made by Merton [10] using artificial neural networks (ANN). Tsai and Wu [15] used many categorisation models to apply a model that was comparable to parametric modelling. When compared to a single classification model, this approach performs poorly. Researchers have been using ANN models extensively, and they show promise as one of the most popular modelling methods [2], [8], [9].

Several researchers use machine learning techniques to model credit risk [2], [3], [16]–[19], to obtain the most appropriate approach according to certain conditions, situations, and types of industries. Many studies use various techniques and methodologies to predict financial distress, producing varying results. Although many financial distress predictions have been conducted and well-studied, there has been little research on SMEs, especially using time factors and the use of deep learning techniques. The purpose of this study is to use deep learning and machine learning algorithms to anticipate the credit rating prospects of SMEs in one year and to offer a financial distress prediction model that takes into account the time variable [11], [12]. This study assesses the credit rating prospects by modelling the financial distress of SMEs, where bankruptcy or default does not always occur, in contrast to other studies that focus on the probability of default. The time element is added to the historical features, sales, and asset changes, in addition to the financial ratio variables.

2. RESEARCH METHOD

This study uses financial report data and the credit history of batik SMEs in Pekalongan city. The variables used are 23 independent variables to classify financial difficulties over a period of three consecutive years. Comparison of the financial situation of the previous fiscal year with the current fiscal year, and comparison of credit score declines are used as dependent variables. Classification performance is improved by taking a different variable selection approach. In addition to using financial ratio variables in one-time factors and sales characteristics, asset changes and credit maturity indicators are also used. This study uses a literature review analysis method and financial distress modelling using deep learning algorithms, namely logistic regression (LR), ANN, and long short-term memory (LSTM) [13], [16]–[18]. The independent variables used refer to Altman and Sabato [8], and Arora and Kaur [20], consisting of financial ratios is presented in Table 1. The variables and metrics used as analysis tools can be seen in Table 1.

Table 1. Independent variable used in model estimation

Measure	Metric
Profitability	Net profit margin, gross profit margin
Leverage	Debt-to-equity-ratio
Activity	Receivable turnover ratio
Liquidity	Current ratio, cash ratio, and quick ratio
Coverage	Asset coverage ratio, debt-service-coverage-ratio
Additional variable	Company age, historical overdue, change in short-term assets, and change in sales

Data modeling using the ANN algorithm. ANN is a classification model using human brain representation. ANN consists of input, output, and intermediary layers. The Y value (dependent variable) is calculated by multiplying the weight by the input and is used in (1).

$$Y_k = w_0 + \sum j = 1^n w_{jk}\ xj \tag{1}$$

Y_k is the input weighted signal from node k, w_0 is the bias value; the connection weight between node k and input j is denoted by w_{jk}; xj is the value of input j, and the number of nodes is denoted by n. The activation function is used to present the weighted sum output. The output value from node k is the result of the activation function as input to the next layer. The activation function is calculated by (2).

$$(Y) = \frac{1}{1+e^{-Y}} \quad (2)$$

Stratified sampling and cross-validation methods, as outlined by Japkowicz and Shah [21] and Chang *et al.* [22] were used for modelling. Butaru *et al*. [2] provided the basis for the classification result thresholds and the choice of cutoff values for various classifiers. Using the Japkowicz and Shah [21] technique, the classifier performance was evaluated without a statistical significance test, as stated by Huang *et al*. [17] and Moscatelli *et al*. [18]. Qu *et al*. [23] defined the confusion matrix technique, which was used to summarise the classification findings. The visualisations of the detection error tradeoff (DET) and receiver operating characteristic (ROC) were based on research conducted by Maldonado *et al.* [24] and Sun *et al*. [25]. Area under the curve (AUC), accuracy measures for confusion matrices, and equal error rate (EER) for ROC and DET graphs were used to assess the model's performance [25]. Utilizing a confusion matrix, the classification model's performance was assessed by computing the AUC and EER for ROC and DET graphs [25]. The financial ratios for assessing SMEs' business portfolios are influenced by several factors such as market sentiment, economic cycles, and industry dominance. The differences in these structures make it interesting for machine learning to recognize the relationship of each case to a particular cluster so as to produce the right classification.

3. RESULTS AND DISCUSSION

The portfolio of batik SMEs assessments that have significant differences from each SME can be identified. Such as differences in liquidity ratios, profitability ratios, and coverage of each batik SME are relatively the same based on the conditions of the batik SMEs. The decline in financial ratios in batik SMEs will be seen by comparing the current year with the previous year. Over the course of a year, Table 2 displays a drop in every liquidity and profitability ratio. However, accounts receivable turnover rates and other business activity indicators demonstrate that batik SMEs are collecting accounts receivable faster and have a lower debt-to-equity ratio.

Table 2. Variable averages based on financial year

Financial ratio category	Specific variable	Financial year
Profitability	Net profit margin	0.50
	Gross profit margin	0.06
Leverage	Debt-to-equity-ratio	1.27
Activity	Receivable turnover ratio	178.15
Liquidity	Current ratio	2.55
	Cash ratio	6.38
	Quick ratio	3.58
Coverage	Asset coverage ratio	4.51
	Debt-service-coverage-ratio	2.98
Additional variable	Change in Sales	0.73%
	Company age	10.8
	Change in short-term assets	0.39%

3.1. Classification results using classic variables

The debt service coverage ratio, asset coverage ratio, cash ratio, current ratio, quick ratio, debt-to-equity ratio, gross margin ratio, profit margin ratio, and receivables turnover ratio are among the conventional parameters that are used in the classification process [8]. The limit values for the LR, ANN, and LSTM classification methods are determined by contrasting each model's median value with the given predictions, as proposed by Addo *et al*. [16]. The proper binomial value is assigned to the modeling findings. There is an overlap in the model, which indicates that there is a classification difficulty in distinguishing the two classes, which results in a negative impact on classification accuracy. This often happens when the learning case is unbalanced [17]. The limit value is set at 0.089 for LR and -0.80 for ANN and LSTM classification.

Based on the harmonic mean and the threshold value set, the ANN classification model produces the highest prediction accuracy of 58.72%. While the performance of LR and LSTM is lower at 2.24 and 1.66 (Tables 3 and 4). When specifically on sensitivity, the positive proportion identification ratio is a key factor for evaluating classification performance on an unbalanced data set, and ANN gets the highest score. Classical predictors are described using ROC and DET, presented in Figure 1. The ROC graph (Figure 1(a)) and DET graphs in Figure 1(b) exhibit the outcomes of the predictor performance evaluation based on the designated threshold value.

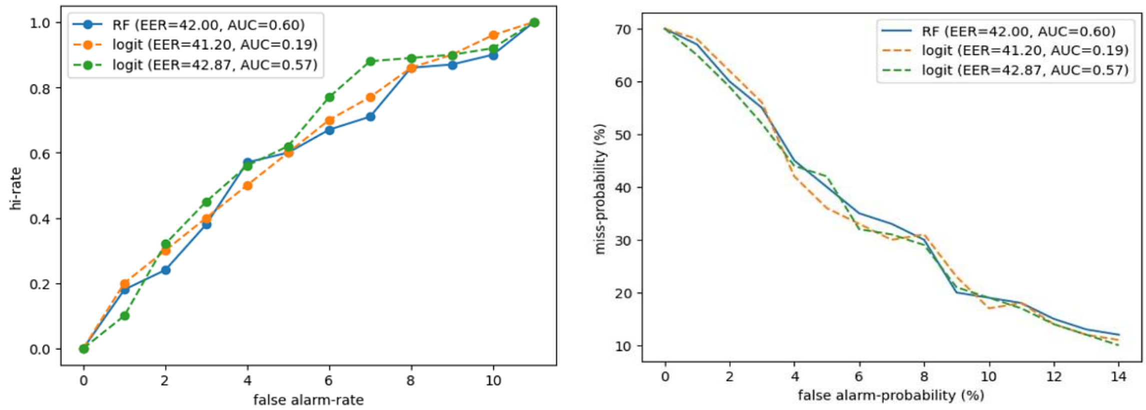
All classification models have overall performance at all limits consistent with the results of the single value limit. The best AUC and EER values are generally shown by the ANN model, which are 0.62 and 41%. While at the extreme limit, the LSTM classification model outperforms ANN, but the overall accuracy is lower, with AUC and EER values of 0.61 and 43%. The lowest accuracy value is obtained by the LR model, which is AUC (0.57) and EER =45%.

Table 3. Performance comparison of classic predictors

Model	Accuracy (%)	Harmonic mean (%)	Average class (%)
LSTM	52.25	56.10	56.59
LR	52.01	55.50	55.91
ANN	52.89	57.82	58.69

Table 4. Detailed confusion matrices for classic predictors

Model	Predicted	Actual negative	Actual positive
LSTM	Negative	5630	5313
	Positive	309	652
LR	Negative	5593	5314
	Positive	317	641
ANN	Negative	5637	5317
	Positive	318	689



(a) (b)

Figure 1. Classic predictor of (a) ROC and (b) DET graphs

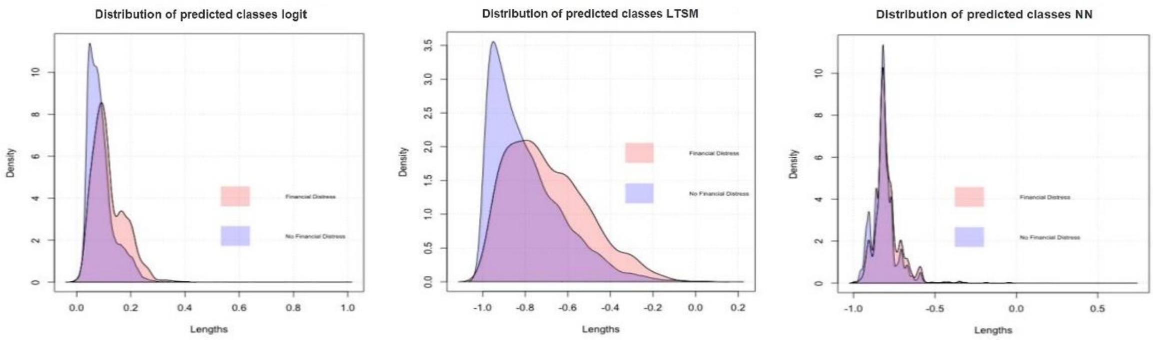
3.2. Classification outcomes including time factor

Next, the model is refined by providing additional indicators of financial distress and time. This addition makes the predictor have a broader perspective, lagging classical variables, historical lags, company age, sales changes, and short-term asset changes. Figure 2 shows that there is a lower overlap of true and predicted classes compared to the classical classification model, and the challenge with imbalanced case prediction remains. The kernel density function graphs for each method used, including logit, are shown in Figure 2(a), LSTM in Figure 2(b), and ANN in Figure 2(c). The threshold values set compared to the classical predictor are relatively similar, with each model's value of 0.08 LR, -0.81 ANN, and -0.83 for LSTM. Shumway stated that period adjustment has a positive risk on the performance of the classification algorithm.

The threshold value and the addition of new independent variables enabled the LSTM model to yield the highest classification accuracy. The harmonic mean value rose to 60.61%, a 2.70 rise. Additionally, the sensitivity ratio went up by 10.16 to 72.4%. The harmonic average of 4.39 for the LR model increased to 60.89%. In contrast, the ANN model's sensitivity ratio dropped by 6.22 to 60.01% and its harmonic mean declined by 2.9 to 55.24%. Figure 3 shows the classification with additional factors using the ROC graph (Figure 3(a)) and DET graph (Figure 3(b)).

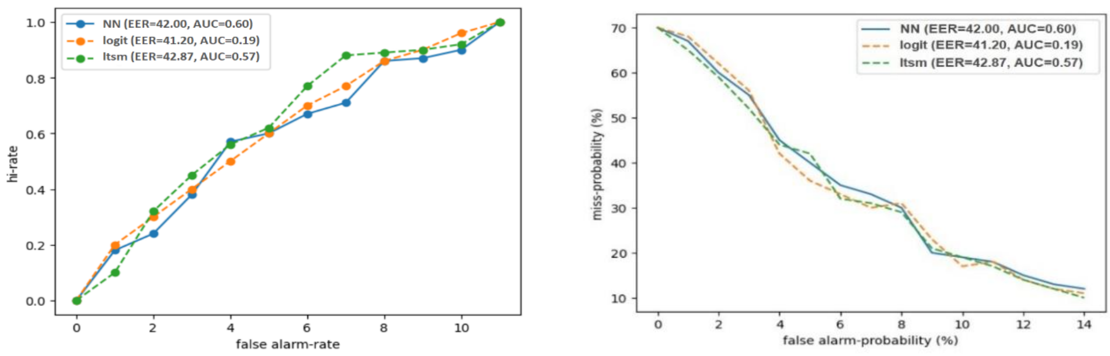
Similar to determining the threshold value, the LSTM model, which has an AUC value of 0.57 and an EER value of 42.87%, is the most accurate model for predicting financial distress. With AUC and EER values of 0.19 and 41.20%, respectively, the LR model achieves the next performance accuracy. The negative impact is experienced by the ANN model with the addition of new variables. The AUC and EER values are lower by -0.03 and +4. The results of the accuracy assessment with the addition of variables are presented in Table 5.

The LR and LSTM classification models increased their accuracy with the addition of new variables. The financial distress prediction model that performed best and had the highest AUC and lowest EER values was LSTM. The LSTM method was also able to identify relational variables based on regular regression beta values and showed the number of incorrect classifications based on variables that were omitted in the classification process. The most important variable that is considered to have a direct impact on the correct case classification is the age of the SME's business. Sun *et.al.* [25] argue that the age of the business is an important variable that will affect financial difficulties.



(a) (b) (c)

Figure 2. Kernel density function graphs showing predicted and actual values of (a) logit, (b) LSTM, and (c) ANN class



(a) (b)

Figure 3. Classifiers with additional factors of (a) ROC and (b) DET graphs

Table 5. Classification results for financial distress predictors

Model	Classic ratio		With additional factor	
	AUC	EER (%)	AUC	EER (%)
LSTM	0.65	43	0.68	38
LR	0.58	44	0.66	38
ANN	0.62	41	0.59	45

3.3. Discussion

Understanding credit risk modelling is crucial for every lender, whether determining the capital requirements set by regulatory bodies or evaluating a borrower's ability to repay a loan. The process gets more difficult when SME-specific issues like limited budgetary flexibility and restricted data availability are taken into account. So an effort is needed to help the process of evaluating lending for SMEs. One thing that needs to be considered is the financial distress that SMEs can experience.

As opposed to the typical default probability predictors, the dependent variable is determined by classifying financial distress when SMEs are experiencing financial distress and not necessarily reaching the final stage of bankruptcy, reflecting the actual lenders' credit decision-making framework. The independent variables are financial factors from the financial strength evaluation categories, including nation identities and liquidity, leverage, profitability, coverage, and activity. These conventional financial ratios were written by Oliver *et al*. [4], Altman and Sabato [8], and Elhoseny *et al*. [11]. With the lowest EER of 41% and the highest AUC value of 0.62, the ANN is the best predictor of financial distress when single-period classical ratio inputs are used. The model correctly categorizes the financial issues in 66% of situations.

The accuracy of the categorization was much improved by the addition of additional independent variables. Ayuni *et al*. [26] state that factors that provide a one-year snapshot of financial ratios were replaced with additional year-time components, lagged history, asset changes, and sales characteristics. By including the best classifier, LSTM, which had the lowest EER of 38% and the highest AUC of 0.68, the prediction sensitivity increased by 6 percentage points to 72%. When compared to LR, ANN, the most effective method for categorizing static periods, saw a 6%-point decrease in sensitivity prediction. Time considerations may be accounted for by the mixed classifiers' response to the empirical part of model construction, which could involve anything from altering training techniques to changing variables [16], [20]. By accounting for the risky period, the time component does, in fact, lower the uncertainty factor, as evidenced by the multi-period categorization's overall superior performance over the static period predictor.

In the best-performing ANN classifier with additional factors, the relevance of each individual variable is equivalent for most variables. The company's age has the highest significance, while the nation indicator has the lowest. The comparatively low significance values for individual variables imply that the interdependence of all variables, rather than the stand-alone components, determines the primary classifier's power. Compared to the traditional default probability classifier, the estimated financial distress predictor has a somewhat lower predictive power of 72%. Other research using default probability modelling, however, shows accuracy levels as high as 85% (even after adjusting for bias).

The different way the dependent variable was formulated could be one of the possible causes of the reduced estimate accuracy. While the focus of traditional credit risk prediction models is on bankruptcy or default, financial distress in this study is defined as a SMEs entity's beginning economic difficulties as shown by changes in credit scores. As the latter phase of a company's life, bankruptcy happens seldom and is triggered by a variety of factors. However, a business can go through multiple instances of financial difficulty without going bankrupt. Events like personnel changes, working capital facility closures, and court conflicts, for instance, can cause short-term financial shocks, even for businesses that have previously demonstrated a low chance of default. From the standpoint of a lender, both would be undesirable due to perhaps increased capital requirements, depending on their risk appetite.

4. CONCLUSION

Understanding how to model credit risk is essential for lenders. The modelling process becomes more difficult to handle, leading to SMEs due to budget constraints and the availability of predictable assets. Unlike typical default prediction, the dependent variable is used to classify financial distress when SMEs experience financial distress and do not necessarily end up in bankruptcy. The independent variables are financial factors from the financial strength evaluation category, including country identity and liquidity, leverage, profitability, coverage, and activity. With the lowest EER of 41% and the highest AUC value of 0.62, the ANN is the best predictor of financial distress when the classic single-period ratio input is used. The model correctly categorizes financial issues in 66% of the situations. The modeling categorization accuracy is much better with the addition of additional independent variables that represent factors such as year, asset changes, and sales characteristics. The sensitivity prediction of the ANN model decreased by 6 percentage points when compared to the LSTM model, which is the best classifier model with an AUC of 0.57 and the lowest EER of 41%. The development of an empirical model by considering the classification response includes variables and modifications to training techniques. The multi-period classification performs better overall than the static period predictor, proving that the time element really reduces the uncertainty factor by accounting for risky times.

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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.

Name of Author	C	M	So	Va	Fo	I	R	D	O	E	Vi	Su	P	Fu
Taryadi	✓	✓	✓	✓	✓	✓			✓	✓		✓	✓	
Bambang Sudiyatno	✓	✓		✓	✓		✓	✓	✓	✓		✓	✓	✓
Robertus Basiya	✓	✓		✓	✓	✓	✓	✓	✓	✓				
Era Yunianto	✓	✓	✓		✓	✓				✓	✓			

C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

The authors state no conflict of interest.

DATA AVAILABILITY

The data supporting the findings of this study are available from the corresponding author, [T], upon reasonable request. To protect participant privacy, in accordance with the ethics approval of the Institute of Widya Pratama Center for Research and Community Service, publicly shareable materials are limited to aggregated results, codebooks, and analysis scripts. Anonymized survey data may be shared under a data use agreement; full interview transcripts are not publicly available.

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