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Comparative Analysis of Machine Learning and Deep Learning Models Integrated with Altman Z-Score for Financial Distress Prediction in Companies Listed on the Indonesia Stock Exchange (IDX)

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ABSTRACT
Financial distress is a condition in which a company experiences a decline in its financial situation, which is typically temporary. However, financial distress can worsen if not promptly addressed, leading to bankruptcy. Early identification of potential financial distress in a company is crucial for stakeholders such as investors, creditors, and regulators. In practice, predicting financial distress in a company is not an easy task. One of the methods commonly used to identify early symptoms of financial distress is the method introduced by Altman in 1986. Altman's research model, known as the Z-Score, determines a value based on standard calculations of financial ratios to indicate the likelihood of a company experiencing bankruptcy. The use of artificial intelligence, such as deep learning, can enhance the scope of research on the analysis and prediction of financial distress. This study aims to conduct a comparative analysis of machine learning models, such as the K-Nearest Neighbor Classifier and Random Forest Classifier, and deep learning models, such as Convolutional Neural Networks (CNN) and Recurrent Neural Networks (RNN). This analysis is carried out to evaluate the success rate of the proposed deep learning models in predicting financial distress in companies operating in Indonesia. Based on the conducted research, the K-Nearest Neighbor Classifier algorithm achieved an accuracy of 77.42% during testing and 88.89% during validation, the Random Forest Classifier algorithm achieved an accuracy of 87.09% during testing and 95.24% during validation, the CNN model achieved an accuracy of 95.16% during testing and 96.83% during validation, and the RNN model achieved an accuracy of 93.55% during testing and 96.83% during validation. Based on these results, the deep learning method has a higher average success rate than machine learning models in predicting financial distress.

INTRODUCTION
The dynamic and complex business world demands continuous growth, adaptation, and strengthening from every entrepreneur and company to face challenges. In the era of globalization

and technological advancements, companies must be capable of dealing with intensified competition, both from local and international firms. Rapid economic growth also brings high risks. Intense competition and rapid market changes can significantly impact the performance and survival of businesses. Therefore, strengthening business units and mitigating risks within the company becomes a necessity to maintain competitiveness and sustain the company's position in an increasingly competitive market.

One of the main risks typically faced by companies is financial difficulty or financial distress. Financial distress refers to the financial condition of a company experiencing a temporary decline in its financial health. However, financial distress can worsen if not promptly addressed and may lead to bankruptcy (Putri, 2021). This risk can occur due to various factors, such as declining revenues, rising production costs, or ineffective business strategies. In cases of financial distress, companies face difficulties in meeting their financial obligations, such as debt repayment or maintaining sufficient liquidity for day-to-day operations. (Sutra & Mais, 2019).

The early identification of potential financial distress in a company is a crucial aspect for stakeholders such as investors, creditors, and regulators. Investors need to consider the risks that may arise in companies within that sector before making investments. Creditors also need to identify this potential financial distress to assess the feasibility of the company before providing loans. Additionally, regulators play a vital role in monitoring market stability and protecting consumer interests from the negative impacts that can arise from financial distress in companies. With these interests in mind, analyzing and predicting financial distress in a company can provide a better understanding of the risks and potential losses that the company may face (Adinda & Musdholifah, 2020).

In practice, predicting financial distress in a company is not an easy task. It has posed a challenge for researchers and academics to find the appropriate and effective methods. One of the methods widely used today to identify early signs of financial distress is the method introduced by Altman in 1986. This research examines the utilization of financial ratios as a tool for predicting financial distress in a company. Altman's research model is also known as the Z-Score, where the value is determined by the standard calculation of financial ratio factors to indicate the likelihood of the company facing bankruptcy (Rifanda et al., 2023).

In recent years, advancements in technology and artificial intelligence have opened new opportunities in the analysis and prediction of financial distress. The utilization of artificial intelligence, such as machine learning and deep learning, can enhance the scope of research in analyzing and predicting financial distress (Elhoseny et al., 2022). Several deep learning models, such as Convolutional Neural Networks (CNN) and Recurrent Neural Networks (RNN), can learn complex patterns and capture non-linear relationships within financial data. By leveraging this capability, deep learning models can be used to predict the potential financial distress of companies with higher accuracy compared to the use of machine learning models.

Based on the background, this research aims to conduct a comparative analysis between machine learning models, such as K-Nearest Neighbor Classifier and Random Forest Classifier, and deep learning models, such as Convolutional Neural Networks (CNN) and Recurrent Neural Networks (RNN). This analysis is conducted to evaluate the success rate of each proposed model in predicting financial distress in companies operating in Indonesia. The data used in this study is obtained from the list of companies listed on the Indonesia Stock Exchange (IDX) from sectors including energy, raw materials, manufacturing, primary consumer goods, non-primary consumer goods, healthcare, property and real estate, technology, infrastructure, and transportation and logistics.

This research focuses on comparing the accuracy levels of each model in identifying the financial condition of companies based on the Altman Z-Score values and categories. By using historical financial statements data of companies from the past five years, specifically from 2018 to 2022, machine learning and deep learning models are trained to classify companies into three categories: safe (no financial distress risk), gray (low financial distress risk), or distress (high potential for financial distress). To conduct this comparative analysis, the accuracy metric is employed to measure the prediction accuracy of each model.

LITERATURE REVIEW

The dynamic and complex business world demands continuous growth, adaptation, and strengthening from every entrepreneur and company to face challenges. In the era of globalization and technological advancements, companies must be capable of dealing with intensified competition, both from local and international firms. Rapid economic growth also brings high risks. Intense competition and rapid market changes can significantly impact the performance and survival of businesses. Therefore, strengthening business units and mitigating risks within the company becomes a necessity to maintain competitiveness and sustain the company's position in an increasingly competitive market.

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Financial Distress

Financial distress refers to the financial difficulties faced by a company before bankruptcy or liquidation (Jason and Prayogo, 2023). Financial distress is typically a temporary condition. If not addressed promptly, it can lead to bankruptcy. The financial condition of a company can be assessed by examining the composition of its balance sheet, comparing the total assets to the total liabilities. This comparison is made when the assets are insufficient or lower in value than the debts. With negative working capital, an imbalance occurs between the company's capital and its debt receivables. This imbalance renders the company incapable of financing its operational activities (Amalia, 2020).

There are several indicators that a company is experiencing financial distress. According to Platt & Platt cited in Putri (2021), these indicators include employee layoffs or the suspension of dividend payments, negative net income from operational activities, negative earnings per share, changes in equity prices, and government-authorized cessation of operations requiring the company to engage in restructuring planning (Putri, 2021). In addition to those indicators, companies often take several actions to address financial distress. These actions may include selling company assets, merging with other companies, and implementing cost-cutting measures to improve their financial situation (Amalia, 2020).

Model Altman Z-Score

The Altman Z-Score model is a numerical measurement model used to predict the likelihood of a business experiencing financial distress or even bankruptcy. This method employs a multiple discriminant analysis (MDA) approach to differentiate between companies facing financial difficulties and those that are not (Pranav et al., 2020). Discriminant analysis is a statistical technique that identifies several financial ratios considered to have significant value in influencing an event. The analysis generates apriori groupings or classifications based on theory or the actual conditions (Ramadhani and Lukviarman, 2009).

METHODS

In this research, several research stages were conducted to analyze the comparison of machine learning and deep learning models in predicting financial distress in companies listed on the Indonesia Stock Exchange (IDX) in the energy, raw materials, manufacturing, primary consumer goods, non-primary consumer goods, healthcare, property and real estate, technology, infrastructure, and transportation and logistics sectors. The research started with problem identification. This initial stage provides an overview of how the research was conducted. The research then proceeded with data collection for the research. Data collection was performed by gathering financial statement data from companies listed on the Indonesia Stock Exchange (IDX) in the energy, raw materials, manufacturing, primary consumer goods, non-primary consumer goods, healthcare, property and real estate, technology, infrastructure, and transportation and logistics sectors. Once the data was collected, the researcher proceeded to the data processing stage. In this stage, the researcher cleaned the data by removing invalid values, calculated the average data for each company over the past 5 years, computed the Altman Z-Score value, and divided the data for training, testing, and validation purposes. The model testing stage was conducted to train each model to recognize patterns and make predictions regarding financial distress. Two machine learning models, K-Nearest Neighbor Classifier and Random Forest Classifier, and two deep learning models, Convolutional Neural Network and Recurrent Neural Network, were utilized. The results of training each model were validated and analyzed in the subsequent stage by comparing the accuracy values of the confusion matrix of each model in predicting financial distress.

RESULTS

DATA COLLECTION

In this research, the data collection stage consists of two phases: collecting data from companies listed on the Indonesia Stock Exchange and retrieving financial statements data from each of those companies. To collect data on companies listed on the Indonesia Stock Exchange, the researcher employed web scraping techniques on the website https://www.sahamu.com/. Through this data retrieval process, a total of 723 stock codes of companies listed on the Indonesia Stock Exchange were obtained.

Figure 1 Collected List of Companies on IDX

```
Total Company:  723
['ENRG.jk', 'MEDC.jk', 'SUGI.jk', 'SURE.jk', 'AKRA.jk', 'BULL.jk', 'GTSI.jk', 'HITS.jk',
'INPS.jk', 'KOPI.jk', 'LEAD.jk', 'MITI.jk', 'MTFN.jk', 'PGAS.jk', 'RAJA.jk', 'SHIP.jk',
'SOCI.jk', 'ADMR.jk', 'ADRO.jk', 'AIMS.jk', 'ARII.jk', 'BOSS.jk', 'BSSR.jk', 'BUMI.jk',
'BYAN.jk', 'COAL.jk', 'CUAN.jk', 'DSSA.jk', 'GEMS.jk', 'GTBO.jk', 'HRUM.jk', 'IATA.jk',
'INDY.jk', 'ITMG.jk', 'KKGI.jk', 'MBAP.jk', 'MCOL.jk', 'PTBA.jk', 'SMMT.jk', 'TOBA.jk',
'TRAM.jk', 'BBRM.jk', 'BESS.jk', 'BIPI.jk', 'BSML.jk', 'CANI.jk', 'CBRE.jk', 'CNKO.jk',
'DWGL.jk', 'FIRE.jk', 'MBSS.jk', 'PSSI.jk', 'PTIS.jk', 'RIGS.jk', 'RMKE.jk', 'SGER.jk',
'TCPI.jk', 'TEBE.jk', 'TPMA.jk', 'APEX.jk', 'ELSA.jk', 'ARTI.jk', 'DEWA.jk', 'DOID.jk',
'HILL.jk', 'ITMA.jk', 'MYOH.jk', 'PKPK.jk', 'PTRO.jk', 'RUIS.jk', 'SICO.jk', 'SMRU.jk',
'SUNI.jk', 'TAMU.jk', 'UNIQ.jk', 'WINS.jk', 'WOWS.jk', 'ADMG.jk', 'AGII.jk', 'BMSR.jk',
'BRPT.jk', 'ESSA.jk', 'FPNI.jk', 'INCI.jk', 'LTLS.jk', 'MDKI.jk', 'MOLI.jk', 'OKAS.jk',
'SBMA.jk', 'SRSN.jk', 'TDPM.jk', 'TPIA.jk', 'UNIC.jk', 'NPGF.jk', 'SAMF.jk', 'AKPI.jk',
'APLI.jk', 'AVIA.jk', 'CHEM.jk', 'CLPI.jk', 'DPNS.jk', 'EKAD.jk', 'KKES.jk', 'OBMD.jk',
```

After obtaining the data from the stock codes of companies listed on the Indonesia Stock Exchange, the next step in the data collection process is to retrieve the financial statements data from each company. The financial statements data from each company is obtained using an API provided by https://financialmodelingprep.com/. The financial statements data used in this research include the income statement and balance sheet. From the income statement and balance sheet data, the researcher will only extract the relevant features such as totalCurrentAssets, totalCurrentLiabilities, totalAssets, retainedEarnings, incomeBeforeTax, totalEquity, and revenue.

Figure 1 Company Financial Report Data Sample

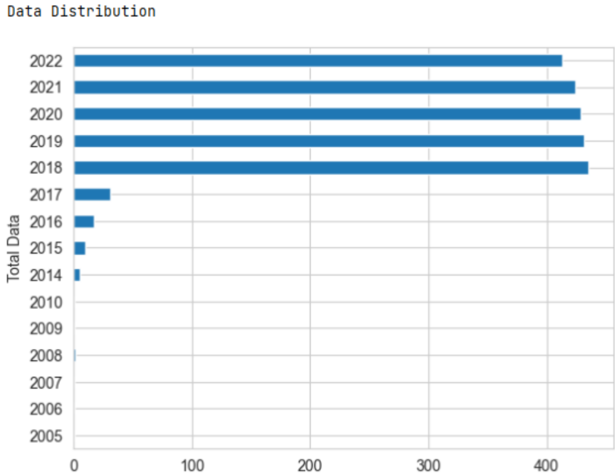
Number of Unique Company 445
Total Row Data 2203
10 Data Financial Report

1-10 2203 rows × 10 columns pd.Dataframe

	date	symbol	incomeBeforeTax	revenue	totalCurrentAssets	totalCurrentLiabilities	totalAssets	retainedEarnings	totalEquity	totalLiabilities
0	2022	ENRG.JK	1.403591e+08	4.519398e+08	1.799896e+08	3.376538e+08	1.194330e+09	-5.192287e+08	5.880092e+08	6.794041e+08
1	2021	ENRG.JK	1.301228e+08	4.060964e+08	1.629583e+08	2.935767e+08	1.063576e+09	-5.859549e+08	5.220569e+08	6.146089e+08
2	2020	ENRG.JK	1.087536e+08	3.248817e+08	1.326495e+08	3.598008e+08	8.446180e+08	-6.262196e+08	3.166020e+08	6.324435e+08
3	2019	ENRG.JK	8.857118e+07	3.343414e+08	1.410806e+08	4.018117e+08	6.793698e+08	-7.279723e+08	2.154630e+08	5.732678e+08
4	2018	ENRG.JK	1.319019e+07	2.734628e+08	1.603652e+08	4.778899e+08	7.314457e+08	-7.559759e+08	1.916711e+08	6.456591e+08
5	2022	MEDC.JK	1.045602e+09	2.312228e+09	1.751396e+09	1.379314e+09	6.931906e+09	9.746901e+08	1.557260e+09	5.184387e+09
6	2021	MEDC.JK	2.857007e+08	1.323242e+09	1.701564e+09	1.006176e+09	5.683884e+09	5.038074e+08	1.072726e+09	4.454548e+09
7	2020	MEDC.JK	-9.828362e+07	1.093274e+09	2.021926e+09	1.372821e+09	5.900823e+09	4.748680e+08	1.025523e+09	4.687438e+09
8	2019	MEDC.JK	1.791461e+08	1.438291e+09	1.694683e+09	7.055810e+08	6.006538e+09	6.732154e+08	1.196458e+09	4.650292e+09
9	2018	MEDC.JK	1.988364e+08	1.218252e+09	1.827115e+09	1.101979e+09	5.252394e+09	7.005630e+08	1.219200e+09	3.865132e+09

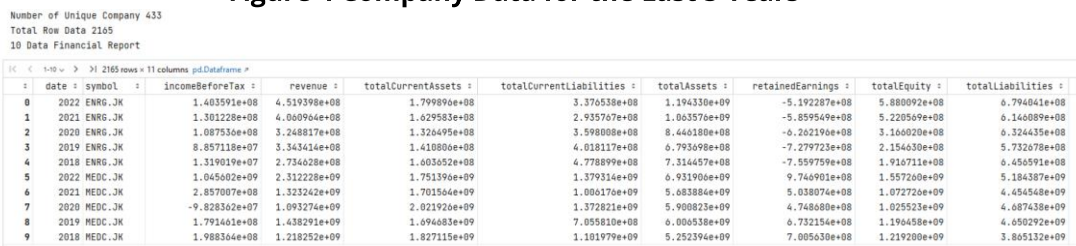
From the retrieval of financial statements data, it was found that data from only 445 companies could be accessed through the API. The total number of rows of financial statements data retrieved using the API is 2203, as shown in Figure 2.

Figure 3. Data Distribution by Year



Next, the collected data is further filtered. From Figure 3, it is evident that out of the 2203 available rows of data, there are still data points that exceed the limit of the past 5 years. Therefore, only the data from companies with complete financial statements within the last 5 years will be retained and used in the analysis.

Figure 4 Company Data for the Last 5 Years



Number of Unique Company 433
Total Row Data 2165
10 Data Financial Report

1-10 2165 rows × 11 columns pd.Dataframe

	date	symbol	incomeBeforeTax	revenue	totalCurrentAssets	totalCurrentLiabilities	totalAssets	retainedEarnings	totalEquity	totalLiabilities
0	2022	ENRG.JK	1.403591e+08	4.519398e+08	1.799896e+08	3.376538e+08	1.194330e+09	-5.192287e+08	5.880092e+08	6.794041e+08
1	2021	ENRG.JK	1.301228e+08	4.060964e+08	1.629583e+08	2.935767e+08	1.063576e+09	-5.859549e+08	5.220569e+08	6.146089e+08
2	2020	ENRG.JK	1.087536e+08	3.248817e+08	1.326495e+08	3.598008e+08	8.446180e+08	-6.262196e+08	3.166020e+08	6.324435e+08
3	2019	ENRG.JK	8.857118e+07	3.343414e+08	1.410806e+08	4.018117e+08	6.793698e+08	-7.279723e+08	2.154630e+08	5.732678e+08
4	2018	ENRG.JK	1.319019e+07	2.734628e+08	1.603652e+08	4.778899e+08	7.314457e+08	-7.559759e+08	1.916711e+08	6.456591e+08
5	2022	MEDC.JK	1.045602e+09	2.312228e+09	1.751396e+09	1.379314e+09	6.931906e+09	9.746901e+08	1.557260e+09	5.184387e+09
6	2021	MEDC.JK	2.857007e+08	1.323242e+09	1.701564e+09	1.006176e+09	5.683884e+09	5.038074e+08	1.072726e+09	4.454548e+09
7	2020	MEDC.JK	-9.828362e+07	1.093274e+09	2.021926e+09	1.372821e+09	5.900823e+09	4.748680e+08	1.025523e+09	4.687438e+09
8	2019	MEDC.JK	1.791461e+08	1.438291e+09	1.694683e+09	7.055810e+08	6.006538e+09	6.732154e+08	1.196458e+09	4.650292e+09
9	2018	MEDC.JK	1.988364e+08	1.218252e+09	1.827115e+09	1.101979e+09	5.252394e+09	7.005630e+08	1.219200e+09	3.865132e+09

From Figure 4 it is observed that out of the 2203 rows of data collected, only 2165 rows of data from 433 companies will be used in the research. These data will undergo further preprocessing in the data preparation stage to make them ready for model training.

Data Analysis

After collecting the data and going through the preprocessing stage, the data analysis phase is conducted to understand the characteristics of the data used in the research. Descriptive analysis performed on the data provides important information about the data's characteristics using various statistical metrics. These metrics include mean, median, mode, max, min, and standard deviation. The mean provides an overview of the average value of the data, while the median represents the middle value unaffected by outliers. The mode identifies the most frequently occurring value in the data. Max and min provide information about the highest and lowest extreme values in the data. Standard deviation measures the extent to which the data is spread out from the mean. By utilizing these metrics, descriptive analysis provides a deeper understanding of the characteristics of the data used in the research.

Table 1. Safe Label Descriptive Statistic

	wcta	reta	ebitta	bvetl	sta	z-score
Mean	0.349177	0.366385	0.123554	3.522334	1.255937	4.709016
Median	0.343857	0.386757	0.090020	2.871797	0.987716	4.387624
Mode	-0.219701	-0.55295	-0.09867	0.160629	0.009463	2.992805
Max	0.783960	0.931470	0.576140	11.686687	7.290643	8.420879
Min	-0.219701	-0.55295	-0.09867	0.160629	0.009463	2.992805
Std. Dev	0.202098	0.269770	0.114970	2.446790	1.155381	1.369662

Table 2 Grey Label Descriptive Statistic

	wcta	reta	ebitta	bvetl	sta	z-score
Mean	0.156847	0.197717	0.054225	1.527230	0.822214	2.382512
Median	0.135354	0.216309	0.044556	1.250873	0.741908	2.397678
Mode	-0.177536	-1.55112	-0.05869	0.112547	0.032943	1.881224
Max	0.609692	0.623650	0.196387	6.316711	2.416781	2.961659
Min	-0.177536	-1.55112	-0.05869	0.112547	0.032943	1.881224
Std. Dev	0.149578	0.252987	0.049322	1.030870	0.551340	0.322939

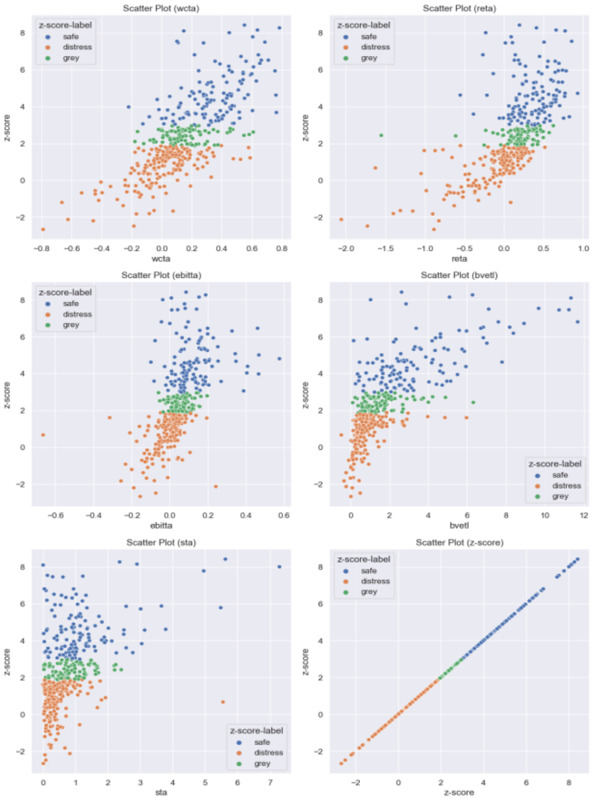
Table 3 Distress Label Descriptive Statistic

	wcta	reta	ebitta	bvetl	sta	z-score
Mean	0.010084	-0.12653	-0.01416	0.807207	0.452941	0.725496
Median	0.023360	0.002562	0.004714	0.661378	0.339470	1.045816
Mode	-0.788971	-2.05636	-0.66464	-0.47327	0.008935	-2.66900
Max	0.588691	0.517115	0.242197	5.966953	5.552567	1.879009
Min	-0.788971	-2.05636	-0.66464	-0.47327	0.008935	-2.66900
Std. Dev	0.196784	0.396179	0.087335	0.788193	0.518489	0.960688

Based on the analysis of the three descriptive statistical tables for the labels safe, grey, and distress, several conclusions can be drawn regarding the mean, median, maximum and minimum values, and standard deviation. The mean values indicate the average of the data for each label. From the tables, it can be observed that the safe label tends to have higher mean values overall compared to the other labels. The median values represent the middle value of the data and can provide insights into the data distribution. Significant variations between the median and mean values are found for some features in each label, indicating skewness or imbalance in the data distribution. The maximum and minimum values reveal the range of values present in the data. Some features exhibit a wide range of values, especially in the safe label, indicating significant variation between the highest and lowest values in the data. The standard deviation represents the extent to which the data is spread out from the mean. The tables demonstrate that the level of variability between features also differs among the labels, with the distress label tending to have higher standard deviation values. This suggests that the data in that label has greater variability and is more spread out. These conclusions provide an understanding of the differences in characteristics and data distribution among the labels safe, grey, and distress based on the mean, median, maximum, and minimum values, and standard deviation.

From Figure 5, which illustrates the distribution of data for each variable against the Z-Score value, it is evident that there is a positive correlation between the values of each data variable and the Z-Score. This indicates that as the values of variables such as WCTA, RETA, EBITTA, BVETL, and STA increase, the Z-Score tends to increase as well. The distribution of data moving in the same direction suggests a positive relationship between these variables and the Z-Score.

Figure 5 Distribution of the Altman Z-Score with the Z-Score value



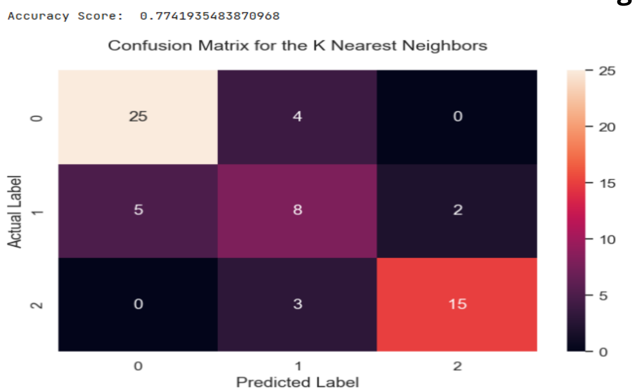
Model Testing

In this stage, the machine learning models, K-Nearest Neighbor Classifier and Random Forest Classifier, as well as the deep learning models, Convolutional Neural Network (CNN), and Recurrent Neural Network (RNN), are trained using the testing data. The models are evaluated by comparing the accuracy values obtained from the confusion matrix, which helps classify the labels of the Altman Z-Score.

K-Nearest Neighbor Classifier

The K-Nearest Neighbor Classifier model is created using the proposed model. The K-Nearest Neighbor Classifier is configured with a parameter called *n_neighbors* set to 3. This parameter is adjusted based on the number of classes used in the classification. The training process of the K-Nearest Neighbor Classifier model using the training data, which consists of 291 data points, takes approximately 156ms to execute. The execution time is relatively fast because this model does not involve complex training processes; it simply calculates distances and performs classification based on the nearest neighbors.

Figure 6 KNN Classifier Confusion Matrix with Testing Data



From Figure 6, it can be observed that using a testing dataset of 62 data points, the K-Nearest Neighbor Classifier model successfully classified the financial distress labels. The model accurately labeled 25 out of 29 data points for label 0 (distress), 8 out of 15 data points for label 1 (grey), and 15 out of 18 data points for label 2 (safe). The overall performance of the model, as indicated by the confusion matrix, showed a total of 48 True Positive (TP) and True Negative (TN) values out of the 62 data points, with a total of 14 False Positive (FP) and False Negative (FN) values out of the 62 data points.

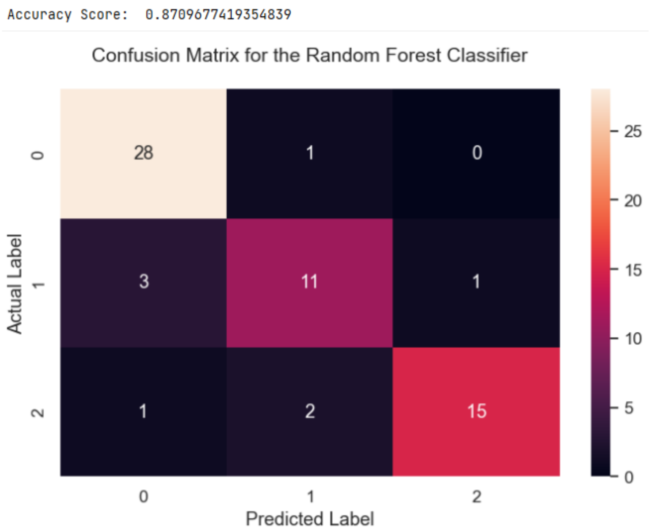
$$accuracy = \frac{TP + TN}{Total\ Data}$$
$$accuracy = \frac{48}{62}$$
$$accuracy = 0.77419$$

Based on the calculation of the accuracy value using the confusion matrix, the accuracy value obtained from testing the K-Nearest Neighbor Classifier model is 0.77419 or 77.42%.

Random Forest Classifier

For the creation of the Random Forest Classifier model, the parameters used are the same as those used for the Decision Tree Classifier. These parameters are *random_state* with a value of 42, and an additional parameter called *n_estimators* with a value of 100, which determines the number of decision trees included in the Random Forest Classifier model. The training process of the Random Forest Classifier model, using a training dataset of 291 data points, takes approximately 289ms for execution. The training time is slightly longer compared to the K-Nearest Neighbor Classifier because the Random Forest Classifier involves constructing multiple decision trees that are later combined.

Figure 7 Random Forest Classifier Confusion Matrix with Testing Data



From Figure 7 provided, it is observed that using a testing dataset of 62 data points, the created Random Forest Classifier model can classify the financial distress label data accurately, with 28 out of 29 data points correctly labeled for label 0 (distress), 11 out of 15 data points correctly labeled for label 1 (grey), and 17 out of 18 data points correctly labeled for label 2 (safe). Furthermore, from the data, it is determined that the total True Positive (TP) and True Negative (TN) values in the confusion matrix amount to 54 out of 62 data points, while the total False Positive (FP) and False Negative (FN) values amount to 8 out of 62 data points.

$$accuracy = \frac{TP + TN}{Total\ Data}$$
$$accuracy = \frac{54}{62}$$

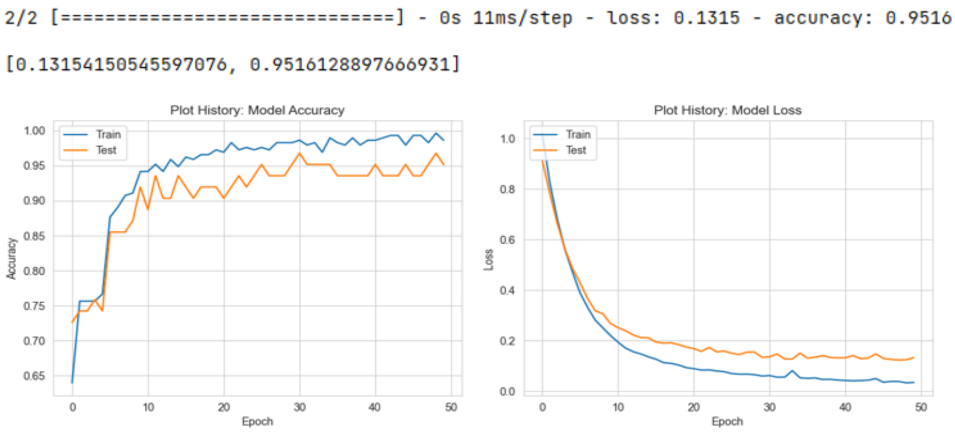
$$accuracy = \ 0.8709$$

Based on the calculation of the accuracy value using the confusion matrix, the accuracy value obtained from testing the Random Forest Classifier model is 0.8709 or 87.09%.

Convolutional Neural Network

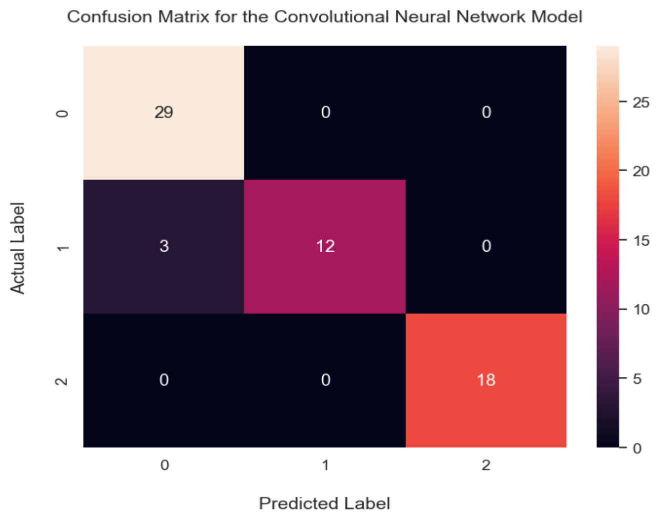
To train the Convolutional Neural Network (CNN) model, the researcher used a total of 291 data points from the training dataset. For the creation and training of the CNN model, the researcher employed 50 epochs with a batch size of 32. The utilization of 50 epochs in training the CNN model allows it to learn complex patterns and make appropriate adjustments to the data. Additionally, a batch size of 32 speeds up the training process and efficiently utilizes computer memory. The training process of the Convolutional Neural Network model with the 291 training data points took approximately 5 seconds and 10 milliseconds to execute. The longer training time is due to the involvement of complex computations such as convolution, pooling, and weight adjustments in each layer of the model.

Figure 8 Convolutional Neural Network Model Training Results



From Figure 8, it is observed that the training and testing accuracy of the Convolutional Neural Network (CNN) model is 0.9516. This accuracy indicates that the model can correctly classify 95.16% of the training data. The loss value obtained from the model training is 0.1315, which means that the average difference between the predicted labels and the actual labels is 13.15%. The training data graph of the Convolutional Neural Network model demonstrates that the model is capable of accurate predictions and can understand patterns in the given data. However, there is a possibility of overfitting in the model.

Figure 9 Convolutional Neural Network Confusion Matrix with Testing Data



From Figure 9, it is observed that using the testing data of 62 instances, the trained Convolutional Neural Network (CNN) model is able to classify the financial distress label with accurate predictions. Specifically, it correctly labeled 29 out of 29 instances for label 0 (distress), 12 out of 15 instances for label 1 (grey), and 18 out of 18 instances for label 2 (safe). Additionally, the confusion matrix shows a total of 59 instances classified as True Positive (TP) or True Negative (TN) out of the 62 instances in total, with a total of 3 instances classified as False Positive (FP) or False Negative (FN).

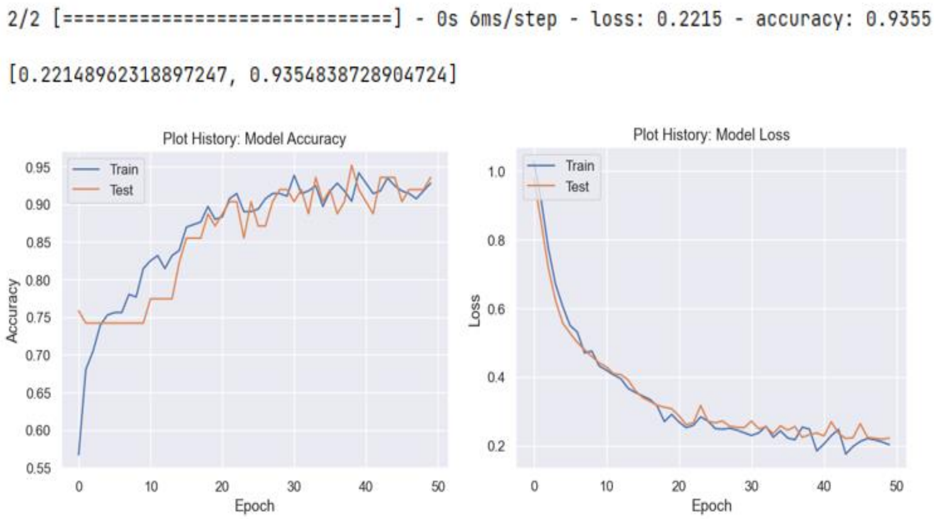
$$accuracy = \frac{TP + TN}{Total\ Data}$$
$$accuracy = \frac{59}{62}$$
$$accuracy = 0.9516$$

Based on the calculation of the accuracy value using the confusion matrix, the accuracy value obtained from testing the Convolutional Neural Network model is 0.9516 or 95.16%.

Recurrent Neural Network

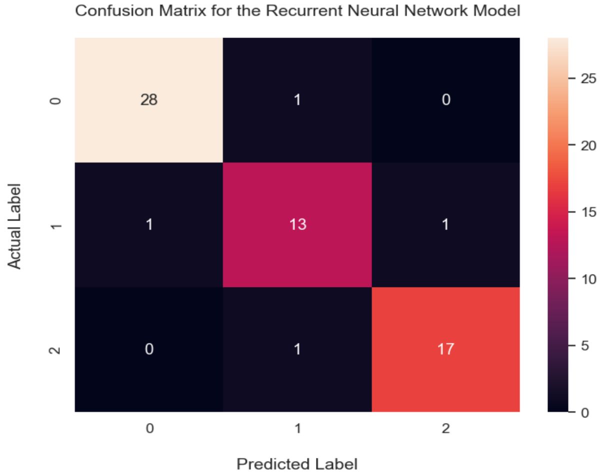
To train the Recurrent Neural Network (RNN) model, the researcher utilized the same training and testing data. The training dataset consisted of 291 instances, while the testing dataset comprised 62 instances. The training parameters used for the RNN model were the same as those employed for the Convolutional Neural Network (CNN) model, namely 50 epochs and a batch size of 32. The training process of the RNN model with the 291 training instances took approximately 6 seconds and 731 milliseconds to complete. The longer training time can be attributed to the repetitive computations performed for each timestep in the sequential data. This process involves recurrent computations and complex backpropagation to generate adequate representations of the sequential data.

Figure 10. Recurrent Neural Network Model Training Results



From Figure 10, it can be observed that the training accuracy achieved by the Recurrent Neural Network (RNN) model, using the training and testing data, is 0.9355. This accuracy indicates that the model correctly classifies 93.55% of the training data. The resulting loss value from the model training is 0.2215, which means the model has an average difference between predicted and actual labels of 22.15%. Similar to the Convolutional Neural Network (CNN) model, the training graph of the RNN model demonstrates its ability to make accurate predictions. However, there is a possibility of overfitting in the model.

Figure 11 Recurrent Neural Network Confusion Matrix with Testing Data



From Figure 11, it is observed that using the testing data consisting of 62 instances, the trained Recurrent Neural Network (RNN) model successfully classified the financial distress labels. The model accurately labeled 28 out of 29 instances for label 0 (distress), 13 out of 15 instances for label 1 (grey), and 17 out of 18 instances for label 2 (safe). Furthermore, the confusion matrix revealed a total of 58 True Positive (TP) and True Negative (TN) instances out of the 62 testing data, with a total of 3 False Positive (FP) and False Negative (FN) instances.

$$accuracy = \frac{TP + TN}{Total\ Data}$$

$$accuracy = \frac{58}{62}$$

$$accuracy = 0.9355$$

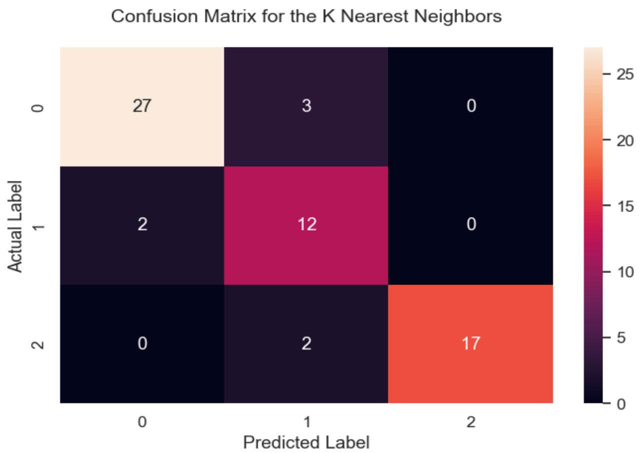
Based on the calculation of the accuracy value using the confusion matrix, the accuracy value obtained from testing the Recurrent Neural Network model is 0.9355 or 93.55%.

Model Validation

In this stage, the results of training the models using the provided training and testing data are compared with the validation data. The validation of the models is performed by comparing the accuracy values obtained from the confusion matrix. The accuracy is calculated by dividing the number of correct label classifications by the total number of data points used in the validation process.

K-Nearest Neighbor Classifier

Figure 12 K-Nearest Neighbor Classifier Confusion Matrix with Validation Data



From Figure 12, it can be observed that the K-Nearest Neighbor Classifier model accurately classified 27 out of 30 actual instances for label 0 (distress), 12 out of 14 actual instances for label

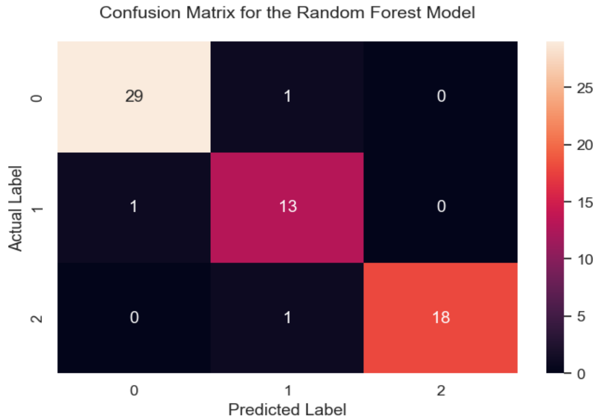
1 (grey), and 17 out of 19 actual instances for label 2 (safe). Out of the total 63 validation data points, the confusion matrix shows that there were 56 instances of True Positive (TP) and True Negative (TN), while there were 7 instances of False Positive (FP) and False Negative (FN).

$$accuracy = \frac{TP + TN}{Total\ Data}$$
$$accuracy = \frac{56}{63}$$
$$accuracy = 0.8889$$

Based on the calculation of the accuracy value using the confusion matrix, the accuracy value obtained from the validation of the K-Nearest Neighbor Classifier model can correctly predict the financial distress label of 0.8889 or 88.89%.

Random Forest Classifier

Figure 13 Random Forest Classifier Confusion Matrix with Validation Data



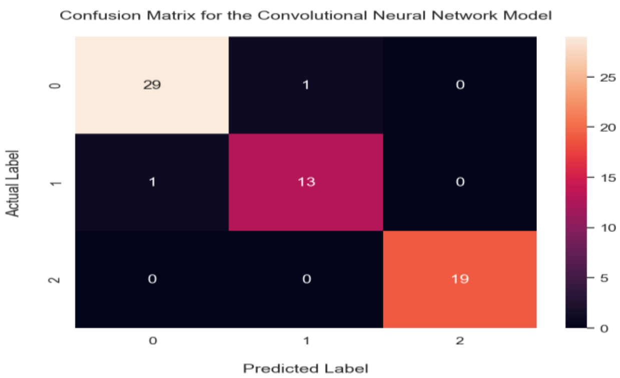
From Figure 13, it can be observed that the Random Forest Classifier model accurately classified 29 out of 30 actual instances for label 0 (distress), 13 out of 14 actual instances for label 1 (grey), and 18 out of 19 actual instances for label 2 (safe). Out of the total 63 validation data points, the confusion matrix shows that there were 60 instances of True Positive (TP) and True Negative (TN), while there were 3 instances of False Positive (FP) and False Negative (FN).

$$accuracy = \frac{TP + TN}{Total\ Data}$$
$$accuracy = \frac{60}{63}$$
$$accuracy = 0.9524$$

Based on the calculation of the accuracy value using the confusion matrix, the accuracy value obtained from the validation of the Random Forest Classifier model can correctly predict the financial distress label of 0.9524 or 95.24%.

Convolutional Neural Network

Figure 14 Convolutional Neural Network Confusion Matrix with Validation Data



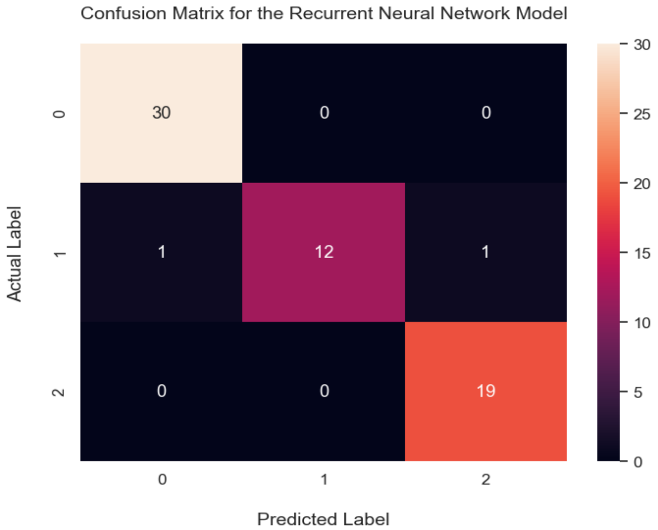
From Figure 14, it is evident that the Convolutional Neural Network model accurately classified 29 out of 30 actual instances for label 0 (distress), 13 out of 14 actual instances for label 1 (grey), and all 19 actual instances for label 2 (safe). Out of the total 63 validation data points, the confusion matrix indicates that there were 61 instances of True Positive (TP) and True Negative (TN), while there were 2 instances of False Positive (FP) and False Negative (FN).

$$accuracy = \frac{TP + TN}{Total\ Data}$$
$$accuracy = \frac{61}{63}$$
$$accuracy = 0.9683$$

Based on the calculation of the accuracy value using the confusion matrix, the accuracy value obtained from the validation of the Convolutional Neural Network model can correctly predict the financial distress label of 0.9683 or 96.83%.

Recurrent Neural Network

Figure 15 Recurrent Neural Network Confusion Matrix with Validation Data



From Figure 15, it can be observed that the Recurrent Neural Network model accurately classified all 30 actual instances for label 0 (distress), 12 out of 14 actual instances for label 1 (grey), and all 19 actual instances for label 2 (safe). Out of the total 63 validation data points, the confusion matrix reveals a total of 61 instances of True Positive (TP) and True Negative (TN), while there were 2 instances of False Positive (FP) and False Negative (FN).

$$accuracy = \frac{TP + TN}{Total\ Data}$$
$$accuracy = \frac{61}{63}$$
$$accuracy = 0.9683$$

Based on the calculation of the accuracy value using the confusion matrix, the accuracy value obtained from the validation of the Recurrent Neural Network model can correctly predict the financial distress label of 0.9683 or 96.83%.

Analysis of Evaluation Results

The evaluation results of the Altman Z-Score values using various machine learning models, namely K-Nearest Neighbor Classifier, Random Forest Classifier, Convolutional Neural Network (CNN), and Recurrent Neural Network (RNN), have led to several conclusions.

Table 4. Comparison of Model Training Time

Model	Training Time
K-Nearest Neighbor Classifier	156ms
Random Forest Classifier	289ms
Convolutional Neural Network	5s 10ms
Recurrent Neural Network	6s 731ms

Table 5 Comparison of Accuracy of each Model

Model	Testing Data Accuracy	Validation Data Accuracy	Average Accuracy
K-Nearest Neighbor Classifier	77.42%	88.89%	83.16%
Random Forest Classifier	87.09%	95.24%	91.17%
Convolutional Neural Network	95.16%	96.83%	95.99%
Recurrent Neural Network	93.55%	96.83%	95.19%

Based on the testing results conducted on the four classification models for predicting financial distress based on Altman Z-Score categories, namely K-Nearest Neighbor Classifier, Random Forest Classifier, Convolutional Neural Network (CNN), and Recurrent Neural Network (RNN), several conclusions can be drawn. Firstly, the K-Nearest Neighbor Classifier exhibits a short training execution time of 156ms, but with relatively low accuracy rates, namely 77.42% for testing and 88.89% for validation. This indicates the limitations of the K-Nearest Neighbor Classifier model in handling the complexity and patterns within financial statement data.

Furthermore, the Random Forest Classifier model requires an execution time of 289ms and demonstrates a significant improvement in prediction accuracy, achieving 87.09% for testing and 95.24% for validation. This model proves to be effective as it combines multiple decision trees, thereby overcoming the limitations of the K-Nearest Neighbor Classifier and providing better predictions for complex data patterns.

The Convolutional Neural Network (CNN) model exhibits excellent performance in predicting financial distress based on the Altman Z-Score category, despite its overfitting and relatively longer execution time of 5s 10ms. It achieves a testing accuracy of 95.16% and a validation accuracy of 96.83%. CNN is capable of extracting important features from financial statement data, particularly in identifying distinctive patterns and characteristics. This makes CNN a strong choice for predicting financial distress based on the Altman Z-Score.

Lastly, the Recurrent Neural Network (RNN) also exhibits overfitting and a relatively longer execution time, taking 6s 731ms to complete. However, it delivers favorable results with a testing accuracy of 93.55% and a validation accuracy of 96.83%. RNN has the advantage of modeling sequential data, enabling it to remember previous information and integrate it into the decision-making process. In the context of Altman Z-Score prediction, RNN is capable of providing more accurate predictions compared to the use of traditional machine learning models.

From the conducted research, the Convolutional Neural Network (CNN) and Recurrent Neural Network (RNN) models exhibit the possibility of overfitting and require longer training time compared to the K-Nearest Neighbor Classifier and Random Forest Classifier models. However, CNN and RNN demonstrate excellent performance in predicting financial distress based on the Altman Z-Score category, achieving high levels of accuracy. On the other hand, the K-Nearest Neighbor Classifier has the shortest training time but relatively lower accuracy. The Random Forest Classifier falls in between, with moderate training time and a significant improvement in accuracy. When selecting an appropriate model, it is essential to consider the balance between the complexity of the data, training time, and desired prediction performance. However, the CNN and RNN models, which utilize neural network approaches, show promising abilities in classifying financial data with significant spatial or sequential structures.

CONCLUSION

Based on the conducted experiments, it can be concluded that predicting financial distress using deep learning in companies listed in the sectors of energy, raw materials, manufacturing, primary consumer goods, non-primary consumer goods, healthcare, property and real estate, technology, infrastructure, and transportation and logistics on the Indonesia Stock Exchange (IDX) is feasible. This research has also successfully implemented machine learning models such as K-Nearest Neighbor Classifier and Random Forest Classifier, as well as deep learning models such as Convolutional Neural Network (CNN) and Recurrent Neural Network, to predict the Altman Z-Score values for predicting financial distress in companies listed on the Indonesia Stock Exchange (IDX).

Based on the conducted research, the prediction of financial distress using the K-Nearest Neighbors Classifier machine learning model yielded an accuracy rate of 77.42% for testing and 88.89% for validation. On the other hand, utilizing the Random Forest Classifier model resulted in an accuracy rate of 87.09% for testing and 95.24% for validation.

For the usage of deep learning models, the Convolutional Neural Network achieved an accuracy rate of 95.16% for testing and 96.83% for validation. On the other hand, the Recurrent Neural Network model yielded an accuracy rate of 93.55% for testing and 96.83% for validation.

The usage of deep learning models has demonstrated an advantage in predicting financial distress among companies listed on the Indonesia Stock Exchange (IDX) compared to machine learning models, based on the average percentage values obtained. Although the Random Forest Classifier model also performed well, deep learning models such as CNN and RNN are preferred choices. Deep learning models have complex architectures that enable them to access patterns, features, and variations in the dataset more effectively. CNN has the ability to learn complex patterns and in-depth characteristics from the data, resulting in higher average percentages. On the other hand, RNN has the advantage of considering the previous context, allowing it to learn relevant patterns more efficiently, even with fewer data. Although deep learning models require longer training times due to their complexity, the results obtained demonstrate superior performance in predicting financial distress.

Suggestion

Based on the conducted research, the author would like to provide some suggestions for future researchers. These suggestions include the use of hyperparameter tuning for each model to maximize their performance and minimize the risk of overfitting. Additionally, the utilization of different datasets, other machine learning or deep learning models, and more complex methods for predicting financial distress can be explored to test the capabilities of each model further.

REFERENCES

Abdullah, M. (2021) 'The implication of machine learning for financial solvency prediction: an empirical analysis on public listed companies of Bangladesh', *Journal of Asian Business and*

Economic Studies, 28(4), pp. 303–320. Available at: https://doi.org/10.1108/JABES-11-2020-0128.

Adinda, A.R. and Musdholifah, M. (2020) 'PENGARUH RASIO KEUANGAN, CORPORATE GOVERNANCE, DAN MAKROEKONOMI TERHADAP FINANCIAL DISTRESS PADA PERUSAHAAN YANG TERDAFTAR DI INDONESIA STOCK EXCHANGE TAHUN 2014-2018', *Jurnal Ilmu Manajemen*, 8(2), pp. 532–548.

Algoritma (2022) *APA ITU SUPERVISED LEARNING?*, *Algoritma*. Available at: https://algorit.ma/blog/supervised-learning-adalah/ (Accessed: 10 June 2023).

Alvian, V. *et al.* (2022) *Klasifikasi Siswa Berprestasi Menggunakan Metode K-Nearest Neighbor (KNN) Pada SMA Negeri 2 Situbondo Classification Of Achieving Students Using K-Nearest Neighbor (KNN) Method At SMA Negeri 2 Situbondo*, *Jurnal Smart Teknologi*. Available at: http://jurnal.unmuhjember.ac.id/index.php/JST.

Alzubaidi, L. *et al.* (2021) 'Review of deep learning: concepts, CNN architectures, challenges, applications, future directions', *Journal of Big Data*, 8(1). Available at: https://doi.org/10.1186/s40537-021-00444-8.

Amalia, S. (2020) *ANALISIS PERBANDINGAN KLASIFIKASI FINANCIAL DISTRESS PERUSAHAAN MENGGUNAKAN SUPPORT VECTOR MACHINE DAN ARTIFICIAL NEURAL NETWORK PADA PERUSAHAAN PERTAMBANGAN 2017-2018*.

Elhoseny, M. *et al.* (2022a) 'Deep Learning-Based Model for Financial Distress Prediction', *Annals of Operations Research* [Preprint]. Available at: https://doi.org/10.1007/s10479-022-04766-5.

Elhoseny, M. *et al.* (2022b) 'Deep Learning-Based Model for Financial Distress Prediction', *Annals of Operations Research* [Preprint]. Available at: https://doi.org/10.1007/s10479-022-04766-5.

Fathurohman, A. (2021) 'MACHINE LEARNING UNTUK PENDIDIKAN: MENGAPA DAN BAGAIMANA', *JURNAL INFORMATIKA DAN TEKNOLOGI KOMPUTER*, 1(3), pp. 57–62.

Haris, M. *et al.* (2021) *Tinjauan Pustaka Sistematis: Implementasi Metode Deep Learning pada Prediksi Kinerja Murid (Implementation of Deep Learning Methods in Predicting Student Performance: A Systematic Literature Review)*, *Jurnal Nasional Teknik Elektro dan Teknologi Informasi* |.

Jain, S. (2017) *When To Use Softmax Activation Algorithm In Deep Learning*, *MPLSVPN - Moving Towards SDN and NFV Based Networks*. Available at: http://www.mplsvpn.info/2017/12/when-to-use-softmax-activation.html (Accessed: 10 June 2023).

Jason, M. and Prayogo, D. (2023) 'PREDIKSI FINANCIAL DISTRESS PADA PERUSAHAAN TERBUKA DI SEKTOR KONSTRUKSI DAN PROPERTI YANG TERDAFTAR DI BURSA EFEK INDONESIA DENGAN METODE INTEGRASI DIFFERENTIAL EVOLUTION DAN LEAST SQUARES SUPPORT VECTOR MACHINE', *Dimensi Utama Teknik Sipil*, 10(1), pp. 77–85. Available at: https://doi.org/10.9744/duts.10.1.77-85.

Kandel, I. and Castelli, M. (2020) 'Transfer learning with convolutional neural networks for diabetic retinopathy image classification. A review', *Applied Sciences (Switzerland)*. MDPI AG. Available at: https://doi.org/10.3390/app10062021.

Loren, R.R., Prayogo, D. and Budiman, J. (2022) 'PREDIKSI KEBANGKRUTAN DENGAN METODE ANN, SVM, DAN CART PADA PERUSAHAAN PROPERTI, KONSTRUKSI, DAN INDUSTRI SEJENIS YANG TERDAFTAR DI BEI', *Dimensi Utama Teknik Sipil*, 9(2), pp. 136–155. Available at: https://doi.org/10.9744/duts.9.2.136-155.

Magdalena, R. *et al.* (2021) 'Klasifikasi Tutupan Lahan Melalui Citra Satelit SPOT-6 dengan Metode Convolutional Neural Network (CNN)', *JEPIN (Jurnal Edukasi dan Penelitian Informatika)* , 7(3), pp. 335–339.

Malakauskas, A. and Lakstutiene, A. (2021) 'Financial distress prediction for small and medium enterprises using machine learning techniques', *Engineering Economics*, 32(1), pp. 4–14. Available at: https://doi.org/10.5755/j01.ee.32.1.27382.

Markoulidakis, I. *et al.* (2021) 'Multiclass Confusion Matrix Reduction Method and Its Application on Net Promoter Score Classification Problem', *Technologies*, 9(4). Available at: https://doi.org/10.3390/technologies9040081.

Moutarde, F. (2018) *Convolutional Neural Network*, *MINES Paris Tech*. Available at: https://people.minesparis.psl.eu/fabien.moutarde/ES_MachineLearning/TP_convNets/convnet-notebook.html (Accessed: 27 May 2023).

Nilsen, A. (2022) 'Perbandingan Model RNN, Model LSTM, dan Model GRU dalam Memprediksi Harga Saham-Saham LQ45', *Jurnal Statistika dan Aplikasinya*, 6(1), pp. 137–147.

Normawati, D. and Prayogi, S.A. (2021) *Implementasi Naïve Bayes Classifier Dan Confusion Matrix Pada Analisis Sentimen Berbasis Teks Pada Twitter*, *Jurnal Sains Komputer & Informatika (J-SAKTI*.

Nwankpa, C. *et al.* (2018) 'Activation Functions: Comparison of trends in Practice and Research for Deep Learning'. Available at: http://arxiv.org/abs/1811.03378.

Pramunendar, R.A., Prabowo, D.P. and Megantara, R.A. (2022) 'METODE RECURRENT NEURAL NETWORK (RNN) DENGAN ARSITEKTUR LSTM UNTUK ANALISIS SENTIMEN OPINI PUBLIK TERKAIT VAKSIN COVID-19', *JURNAL INFORMATIKA UPGRIS*, 8(1), pp. 44–48.

Pranav, N.S.V.N.S.P.R. *et al.* (2020) 'ALTMAN AND OHLSON MODEL IN PREDICTING DISTRESS OF INDIAN COMPANIES: A COMPARISON OF MODELS', *European Journal of Molecular & Clinical Medicine*, 7(8), pp. 4158–4167.

Pratama Agustin, A. and Charis Fauzan, A. (2022) *Implementation Of K-Nearest Neighbor With Minkowski Distance For Early Detection Of Covid-19 In CT-Scan Images Of The Lungs Abstrak*, *Jurnal Ilmiah Intech : Information Technology Journal of UMUS*. Available at: https://ui.adsabs.harvard.edu/abs/2020arXiv200313865Y/abstract.

Puspita Hidayanti, W. (2020) 'Penerapan Algoritma K-Nearest Neighbor Untuk Klasifikasi Efektivitas Penjualan Vape (Rokok Elektrik) pada "Lombok Vape On"', *Jurnal Informatika dan Teknologi*, 3(2).

Putri, A. (2021) 'ANALISIS SPRINGATE (S-SCORE) SEBAGAI ALATUNTUK MEMPREDIKSI FINANCIAL DISTRESSPT.SMARTFREN TELECOM,TbkPERIODE TAHUN 2016-2019', *JIMA Jurnal Ilmiah Mahasiswa Akuntansi*, 1(2), pp. 92–105.

Ramadhani, A.S. and Lukviarman, N. (2009) 'PERBANDINGAN ANALISIS PREDIKSI KEBANGKRUTAN MENGGUNAKAN MODEL ALTMAN PERTAMA, ALTMAN REVISI, DAN ALTMAN MODIFIKASI DENGAN UKURAN DAN UMUR PERUSAHAAN SEBAGAI VARIABEL PENJELAS (STUDI PADA PERUSAHAAN MANUFAKTUR YANG TERDAFTAR DI BURSA EFEK INDONESIA)', *Jurnal Siasat Bisnis*, 13(1), pp. 15–28.

Ratan, P. (2020) *What is the Convolutional Neural Network Architecture?*, *Analytics Vidhya*. Available at: https://www.analyticsvidhya.com/blog/2020/10/what-is-the-convolutional-neural-network-architecture/ (Accessed: 27 May 2023).

Rezkia, S.M. and Widya, A. (2021) *Yuk Kenali Jenis-jenis Algoritma Unsupervised Learning*, *DQLab*. Available at: https://dqlab.id/yuk-kenali-jenis-jenis-algoritma-unsupervised-learning (Accessed: 10 June 2023).

Rifanda, A., Yuwandhani, P. and Rizal, N.A. (2023) *Analisis Rasio Keuangan Untuk Memprediksi Financial Distress Menggunakan Support Vector Machine Financial Ratio For Predicting Financial Distress Using Support Vector Machine*.

Roihan, A., Abas Sunarya, P. and Rafika, A.S. (2019) 'Pemanfaatan Machine Learning dalam Berbagai Bidang: Review paper', *IJCIT (Indonesian Journal on Computer and Information Technology)*, 5(1), pp. 75–82.

Rustam, Z. *et al.* (2020) 'Analysis of Architecture Combining Convolutional Neural Network (CNN) and Kernel K-Means Clustering for Lung Cancer Diagnosis', 10(3).

Saleem, M.A. *et al.* (2022) 'Comparative Analysis of Recent Architecture of Convolutional Neural Network', *Mathematical Problems in Engineering*, 2022. Available at: https://doi.org/10.1155/2022/7313612.

Santoso, R.R., Megasari, R. and Hambali, Y.A. (2020) 'Implementasi Metode Machine Learning Menggunakan Algoritma Evolving Artificial Neural Network Pada Kasus Prediksi Diagnosis Diabetes Implementation of Machine Learning Method Using Evolving Artificial Neural Network Algorithm in Prediction of Diabetes Diagnosis', *JATIKOM: Jurnal Aplikasi dan Teori Ilmu Komputer*, 3(2), pp. 85–97. Available at: https://ejournal.upi.edu/index.php/JATIKOM.

Saputra, F.B. and Fatimah (2022) 'Indikasi Financial DistressMenggunakan Model Altman Z-Score pada Perusahaan Sub Sektor Rokok yang Terdaftar di Bursa Efek Indonesia (BEI) Periode 2017-2021', in *Prosiding SNAM PNJ*, pp. 1–10.

Siswoyo, B. *et al.* (2019) 'MACHINE LEARNING PREDIKSI KEBANGKRUTAN MENGGUNAKAN ALTMAN Z-SCORE', *Buffer Informatika*, 5(1). Available at: https://doi.org/10.25134/buffer.v5i1.1955.

Siswoyo, B. *et al.* (2022) 'Ensemble machine learning algorithm optimization of bankruptcy prediction of bank', *IAES International Journal of Artificial Intelligence*, 11(2), pp. 679–686. Available at: https://doi.org/10.11591/ijai.v11.i2.pp679-686.

Supriyadi, R. *et al.* (2020) 'Penerapan Algoritma Random Forest Untuk Menentukan Kualitas Anggur Merah', *Jurnal Ilmiah Ekonomi dan Bisnis*, 13(2), pp. 67–75. Available at: http://journal.stekom.ac.id/index.php/E-Bisnis■page67.

Sutra, F. and Mais, R. (2019) 'FAKTOR-FAKTOR YANG MEMPENGARUHI FINANCIAL DISTRESS DENGAN PENDEKATAN ALTMAN Z-SCORE PADA PERUSAHAAN PERTAMBANGAN YANG TERDAFTAR DI BURSA EFEK INDONESIA TAHUN 2015-2017', *Jurnal Akuntansi dan Manajemen*, 16(1), pp. 35–72.

Tarkus, E.D., Sompie, S.R.U.A. and Jacobus, A. (2020) 'Implementasi Metode Recurrent Neural Network pada Pengklasifikasian Kualitas Telur Puyuh', *Jurnal Teknik Informatika*, 15(2), pp. 137–144.

Tran, K.L. *et al.* (2022) 'Explainable Machine Learning for Financial Distress Prediction: Evidence from Vietnam', *Data*, 7(11). Available at: https://doi.org/10.3390/data7110160.

Trivusi (2022) *Yuk Kenali Apa itu Algoritma K-Nearest Neighbors (KNN)*, *Trivusi*. Available at: https://www.trivusi.web.id/2022/06/algoritma-knn.html (Accessed: 23 June 2023).

Wall Street Prep (2023) *Nilai Buku Ekuitas (BVE)*, *Wall Street Prep*. Available at: https://www.wallstreetprep.com/knowledge/book-value-of-equity/ (Accessed: 26 June 2023).

Wu, D., Ma, X. and Olson, D.L. (2022) 'Financial Distress Prediction Using Integrated Z-Score and Multilayer Perceptron Neural Networks', *Decis. Support Syst.*, 159(C). Available at: https://doi.org/10.1016/j.dss.2022.113814.

Yiu, T. (2019) *Understanding Random Forest*, *Towards Data Science*. Available at: https://towardsdatascience.com/understanding-random-forest-58381e0602d2 (Accessed: 10 June 2023).

Zheng, Y. *et al.* (2014) 'Time Series Classification Using Multi-Channels Deep Convolutional Neural Networks', in *LNCS 8485*, pp. 298–310.