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# Interconnected Stocks Examination for Predicting the Next Day's High on the Indonesian Stock Exchange

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**Abstract:** We observed in many WhatsApp/Telegram Indonesian stock market groups, but we did not find any stock prediction method that utilizes interconnectivity between stocks. In this paper, we examined the interconnected stock dynamics in the IDX and used it to predict the next day's high. We employed a novel method called "Connected Stocks + Rolling Window Method" which uses both the temporal dynamics of the stock market and the interconnectedness of IDX's stocks. We explored the characteristics of the interconnected stocks by implementing three machine learning algorithms - K-nearest Neighbor (KNN), Support Vector Machine (SVM), and Random Forest (RF) - and found valuable insight. The experiment showed that several factors including a balanced threshold model and increased stock input size helped the performance of a model, while several factors including window size, additional features added, and using specific sectors as training data did not help the model's performance. The result also showed that several stocks like ANTM and ERAA show signs of interconnectedness and are influenceable while some like KLBF are hard to influence and show no sign of interconnectedness based on their results. ANTM was able to obtain an accuracy of 65% using Random Forest when trained on multitudes of features, BRPT was able to obtain an average accuracy of 67% on all three machine learning algorithms when using inputs from different sectors, and ERAA reached an average accuracy of 62% when trained using basic features. All of this showcases forms of interconnectedness.

**Keywords:** Stock prediction, machine learning, support vector machine, random forest, indonesian stock market

## 1. INTRODUCTION

Based on our observations on various WhatsApp/Telegram Indonesian stock market groups, no technique was found that explores the connectivity between the listed stocks on the Indonesian Stock Exchange (IDX). This investigation has motivated us to examine the relationships between stocks using a machine learning approach. We assume that there is a hidden connection between stocks on the IDX even if they are in different sectors. These stocks are interconnected, meaning they are influencing each other's dynamic, suggesting each movement affects one another which we aim to leverage in our stock prediction as the main purpose of our research.

The stock market, one of the foundations of the economy, is a marketplace where investors buy and sell stocks. The concept of a stock market works so well, that by having a better understanding of it, you are shown to be able to predict economic cycles [1]. By default, everyone started to try and predict the flow of the stock, and thus the world of stock market prediction came into existence with its ever-growing tool of techniques and models [2].

At first, most tools that are models that people use as a guideline for stock prediction relied for traditional analysis utilizing features and macroeconomic indicators [3]. However, standard machine learning methods became more popular and were starting to be applied in this area due to their capabilities [4]. Several models, such as Random Forest (RF) and Support Vector Machines (SVM) have been used to discern patterns and relationships between stock data [5], [6]. Other models, like logistic regression and K-nearest neighbor (KNN), were mainly implemented due to their effective and simple way of classifying stock price movements [7]. Improvement in the world of stock prediction started to focus on time-series analysis due to how time itself can give context to a stock and that the ability to capture the temporal dynamics of stock price movements shows promise [8]. It can be seen why while traditional methods might have valuable insights, they often struggle to capture the market's volatility and non-linearity which machine learning has shown promise in doing and improving upon [9].

The IDX, when compared to other major stock market indexes of other large countries, has a small market capi-

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talization. Other than that, a study found that specific stock groups in the IDX were found to be volatile, which shows high risks [10]. Another paper found that specifically fiscal impacts were likely ineffective due to the government's usage of paying debt instead of investing showcasing that the country can impact itself negatively in its stock market [11]. Lastly, Purnomo and Rider [12] found that surprisingly foreign stocks like the U.S. or Japan have a very small influence on Indonesia's stock market. All of this shows that IDX has a problem of being a volatile stock market to work with for investors, while also showing that it is not affected by foreign stocks, but instead its own policies and stocks which might be due to its small market capitalization [13].

We examined this issue and used the interconnected stock behavior that's in the IDX to predict the next day's high via binary classification. We predicted whether the next day's high would be higher than 1.5% of today's close to ensure that we have a profit of 1% since the fee in total to pay for trading using Mirae Asset Sekuritas is 0.4%. We implemented a novel method called the "Connected Stocks + Rolling Window" method which captures the temporal dynamic of stocks via rolling window and captures the interconnected stock dynamics via proper sequencing. To ensure that the method works on different types of machine learning models, we employed several machine learning models, such as SVM, KNN, and RF.

Our key contributions are summarized as follows:

- We examined the interconnected property of stocks in IDX by predicting the next day's high of a stock.
- We implemented three different machine learning models to learn the data to ensure that the evaluation results will be generalized. Furthermore, we will gain insight into the characteristics of these three models when being used with potentially interconnected stocks.
- We conducted extensive experiments to find the characteristics of the interconnected stocks in IDX and their ability to predict the next day's high by analyzing different variables/inputs and their impact on the model's ability to predict.

The paper is organized as follows. Section 2 provides an extensive review of related works, showcasing the different ways stock prediction is explored and relevant literature that unmasks the characteristics of the IDX. In Section 3, we show our methodology, including our flowchart, data collection, pre-processing, model training, and evaluation method of our model. In section 4, we describe our lists of experiments and tasks in detail, showcasing the different ways we experiment with the variables to learn the characteristics of the model. Section 5 displays the results of our experiment, with proper discussion to further give an understanding of interconnected stocks, IDX, and the model's performance. In section 6, we conclude the paper by summarizing the main findings and their implications in stock prediction on the IDX.

## 2. RELATED WORKS

### A. *The Stock Market*

The stock market is a complicated area that both reflects and influences economic activities. Engle et al. [14] looked at the connection between stock markets and big economic indicators and found that looking at historical data can help predict how the market might change, especially considering key factors like inflation and industrial production growth. The study found that these key factors work in predicting volatility in both long-term and short-term changes by using different models and showing how closely linked the economy and the stock market are.

Fischer and Merton [1] approached this way of thinking regarding the stock market's role in making investment decisions and its ability to predict economic cycles. By emphasizing the market's potential as a predictor of GNP components and the business cycle, the research challenges the idea that stock market ups and downs are just random noise. It highlights the importance of understanding the relationship between stock prices and investment decisions, considering things like required returns on equity and the cost of capital. Galeotti and Schiantarelli [15] explore the intricate relationship between stock market volatility and investment decisions, comparing fundamental and non-fundamental factors to it. They found that changes in investment are significantly correlated with movements in both fundamental and non-fundamental components of stock prices. However, a significant difference arises in their influence on investment decisions, with fundamentals having a more substantial impact compared to non-fundamentals. These findings emphasize how economic factors and stock market evaluations can influence financial decision-making.

### B. *Machine Learning in Stock Market Prediction*

With the previous explanation and understanding of the stock market, it can be seen why machine learning is a powerful tool within the financial sector, particularly for the prediction and analysis of stock market prices. The utilization of various machine learning paradigms, including supervised and unsupervised algorithms, ensemble methods, time series analysis algorithms, and deep learning models, has become commonplace in addressing stock price prediction challenges [3], [5], [6], [16], [17], [18].

The reason for using machine learning in stock prediction is its ability to use historical stock market data as a valuable source of information. Sonkvade et al. [3] show that their predictive power comes from their ability to apply these patterns to predict future trends, offering valuable insights for making investment decisions. Their adaptability allows them to find subtle and non-linear relationships which help provide understanding on the dynamic nature of stock market movements [3], [7].


Figure 1. Illustration of K-Nearest Neighbor

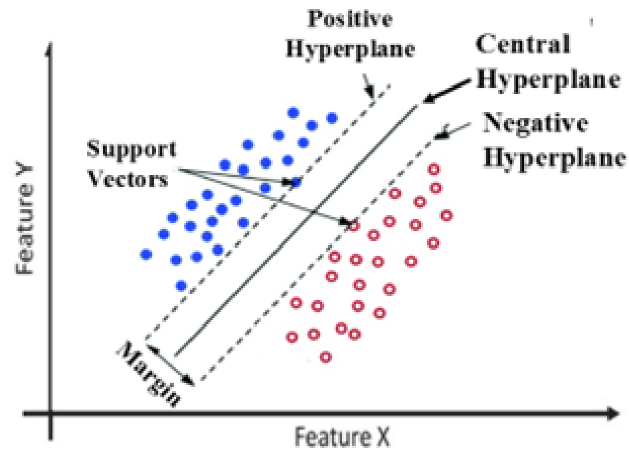


Figure 2. Illustration of Support Vector Machine

Huang et al. [17] did an innovative study on using machine learning for predicting stock prices. By analyzing a comprehensive dataset covering 22 years of quarterly financial data, the study revealed relevant findings based on fundamental analysis. The Random Forest model stood out by providing superior prediction results, proving itself as a powerful tool for forecasting stock prices. When feature selection was applied using Random Forest, it significantly improved the performance of other models where the combination of them into a unified framework even outperformed the benchmark DJIA index during testing regarding their portfolio score. Leung et al. [6] delved into business intelligence (BI) systems and structural support vector machines (SSVMs) for stock price prediction. The paper suggested using a minimum graph cutting algorithm to efficiently solve the optimization problem, drawing parallels between the SSVM's separation oracle and maximum a posteriori (MAP) inference. Their experiment shows the practicality and effectiveness of this method in predicting stock prices achieving higher accuracy compared to many existing systems according to domain experts.

### C. *K-Nearest Neighbor (KNN) in Stock Market*

KNN is a flexible data mining technique widely used for classification tasks. Its core concept involves categorizing an unknown sample by considering the known classifications of its neighboring elements within a training set [19]. KNN, using a specific distance function, selects the k nearest neighbor to the element and classifies the class of the new element based on its neighbors and their distance to the element [20]. The parameter 'k' here denotes the number of neighbors to consider which its example can be seen in Fig. 1, where the illustrations denote two 'k' parameters, which are k = 3 and k = 5.

Subha and Nambi [18] show that KNN finds application in stock market analysis, particularly in prediction and classification tasks. In stock prediction, KNN commonly identifies the k nearest neighbors in the training dataset based on the Euclidean distance from the instance being classified.

Imandoust and Bolandraftar [21] explore the application of the KNN algorithm in economic forecasting, emphasizing its versatility across various domains, including stock market forecasting. Due to its robustness to noisy data, KNN can be effective even with large training datasets, and with its simplicity, effectiveness, and flexibility it can be considered a valuable tool during stock prediction. Subha and Nambi [18] using these advantages of KNN trained their data and explored the predictability of stock index movement using the KNN algorithm while drawing comparisons with the traditional Logistic Regression model. They achieved an overall error score of 20.35% for the KNN Classifier, whereas Logistic Regression had a higher error score of 45.89% showing the effectiveness of the KNN Classifier.

### D. *Support Vector Machines (SVM) in Stock Market*

SVM is a powerful machine learning algorithm widely employed in various domains, including stock market prediction. While originally unpopular, SVM became popular when they showed they could do really well in practical tasks like recognizing digits, understanding images, and sorting text [22], [23]. A big strength of SVM is that it is particularly effective in situations where the relationship between input features and the output is complex and non-linear[22], [24]. The reason for this is that SVM operates by finding a hyperplane that best separates data points into different classes while maximizing the margin between these classes[22], [25]. This can be seen in Fig. 2, where the illustration showcases how having a hyperplane with a maximizing margin can classify large sums of data well [26], [27].

SVMs are well known to be effective at classifying because it is able to find a good balance between two different ways of solving problems [28]. They figure out a straight line for making decisions, but they can also turn the data into a more complex form using something called kernels [25]. The kernel function allows SVM to implicitly map the input features into a higher-dimensional space, making it possible to find a hyperplane that effectively separates the data [22], [25], [29]. Tanveer et al. [30] assessed the utility of SVMs through their efficiency, accuracy, and generalizability. In their comparative analysis, they showed that this algorithm remains competitive only slightly below deep learning models reaching 82.3% compared to 85.2% while having a higher efficiency and can generalize across multiple diverse domains. This is crucial to our model which requires an algorithm that is efficient and generalizable due to the nature of the stock market while also maintaining high accuracy.

SVM has been shown to work well in stock market prediction, proven by it being one of the best models when compared to other models [8], [31]. Ou and Wang [31] did a comparison of ten different data mining techniques to forecast the Hang Seng Index. The study compared multiple data mining techniques, where the result of the comparison shows that SVM is better than all the other models showing its superior predictive powers. Notably, SVM outshines LS-SVM in in-sample prediction, showcasing its advantages in accurately classifying training data which shows how good it is at understanding patterns. Qian [8] compared machine learning models (Logistic Regression, Multilayer Perceptron, and SVM), traditional models (ARIMA and GARCH), and a deep learning model called denoising auto-encoder (DAE) in the S&P 500 index. By using hit ratio and prediction as the evaluation method, they found that compared to other models SVM was the highest reaching 0.642. This paper also shows that SVM is compatible with the deep learning model. When combined, the model was able to achieve the highest hit rate reaching 0.672 showing the capabilities of SVM and its compatibility.

### *E. Random Forest (RF) in Stock Market*

Random forests, as explained by Breiman [32], are an ensemble of decision trees, where each decision tree in the ensemble acts as a base classifier to determine the class label of an unlabeled instance through majority voting which can be seen illustrated by Fig. 3 [33]. Since it is an ensemble model, random forest's results are based on the majority of the results from every decision tree inside of it [34]. Additionally, from Fig. 3, since the model is used for a classification problem, the correct next step in the illustration after processing all decision trees is majority voting because averaging is used on regression problems.

The effectiveness of a random forest depends on the individual trees' strength and their correlation, meaning the rate of convergence from the model depends only on its strong features [35]. Random forests are also good at handling noisy data because they employ a random selection

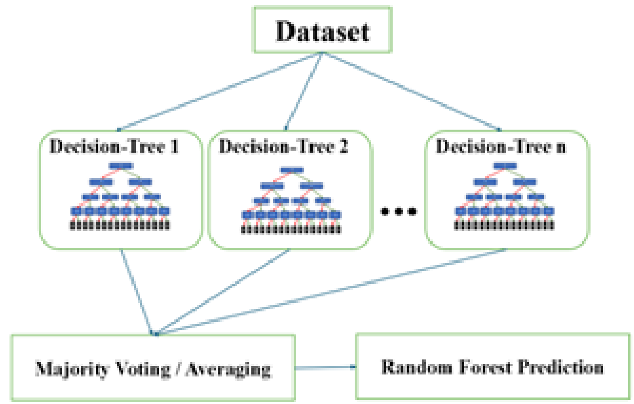


Figure 3. Illustration of Random Forest

of features for node splitting, a feature that distinguishes them favorably from models like Adaboost [32], [35]. Breiman's research shows that random forests consistently perform well, especially when dealing with sparse data [32]. They are good at avoiding overfitting, reducing bias, and matching the accuracy of the Bayes rate on multiple datasets [32], [35].

Due to all of these capabilities, random forest's application is also extended into the realm of stock market prediction [8], [17], [36]. For example, Huang et al. [17] were able to fully capitalize random forest's strength in stock market prediction by combining it with the understanding of fundamental analysis. Random forest as a model was able to beat both Feed-forward Neural Network (FNN) and Adaptive Neural Fuzzy Inference System (ANFIS) showcasing its strength under the right circumstances [17]. Yin et al. [36] gave an example of an optimized random forest model performing efficiently on the stock market. Based on the data from Yahoo Finance, the model used a unique method of optimization called the D-RF-FS method which utilized the decision tree's feature screening to select the most relevant features. They also optimized the model through various methods including random sampling parameterization, exponential smoothing in pre-processing, and 3-fold cross-validation. The optimization improved the model's accuracy in the four stocks compared to the original random forest model and LightGBM model. These optimizations showcase the importance of refining models through proper feature selection, which is the core idea we used to improve our models as well.

### *F. Indonesian Stock Exchange*

Before examining the characteristics of IDX, Table I. was created to show the difference between Indonesia's whole stock market compared to the big U.S. Index stock exchange Nasdaq and DJIA, the Tokyo Stock Exchange's stock market index Nikkei 225, and DAX the index of the 40 major blue-chip companies in the Frankfurt Stock Exchange. Even with only Nasdaq being the stock exchange with a higher stock count than IDX, every single stock market index had a better price compared with IDX. This shows how the Indonesian stocks are smaller compared to other big stock exchanges, meaning that it is easier to be influenced.

There are several studies that try to explore the dynamics and intricacies of the Indonesian stock market. First, Herwany and Febrian [10] did extensive research analyzing the volatility of the Islamic Stock in the IDX and found that it is heavily influenced by macroeconomic indicators during economic downturns. They found that these stocks were highly volatile and found that the risk-return relationship still needs to be researched further due to the current methods not being effective at minimizing the Islamic stocks's risks. Jusoh et al. [11] focused on examining the effects of fiscal and monetary policy in the Indonesian stock market. They found that there's a positive stock price response in regard to monetary policy shocks, while there's a negative stock price response in regard to fiscal policy shocks. This indicates that fiscal policy is ineffective at influencing the economy which the paper suggests due to government spending mainly used for paying debt rather than public finance investments.

Purnomo and Rider [12] had a crucial analysis of the impact of domestic and foreign shocks on the Indonesian stock market. Surprisingly, the paper found that there is no evidence that the Indonesian stock market is cointegrated with the U.S. and Japanese stock market meaning low influence on the market. The paper also finds Indonesia's stock market to be influenced by regional markets meaning they are better stock market predictors compared to foreign stocks. Lastly, Gan Siew Lee and Djauhari [13] investigate 99 blue chip stocks in the IDX using network analysis approach and correlation networks analyzing the market's connectivity. By using a novel centrality measure, the overall centrality measure, which is the optimal linear combination of traditional centrality measures to summarize important information in the IDX, they were able to find high scoring stocks.

From these studies, it can be seen that there's evidence of volatility in the IDX [10], closely-related stocks [13], the government's policy has an impact on the stock market [11], and it is unlikely to be influenced by foreign shocks [12]. These strings of potential reasons on the behavior of the Indonesian stock market show promise in examining the connections between stocks in the IDX.

Based on our observation in reviewing literature, it can be observed how they connect to the creation of our methods. Through Galeotti and Schiantarelli [15], it can be seen that intricate connections in the stock market is hidden in its volatility. Several research shows machine learning models such as SVM, KNN, and RF performing well on stock market predictions [8], [17], [21], [31]. Then when analyzing IDX, there's several characteristics that hints at our assumptions. As previously mentioned, they show that

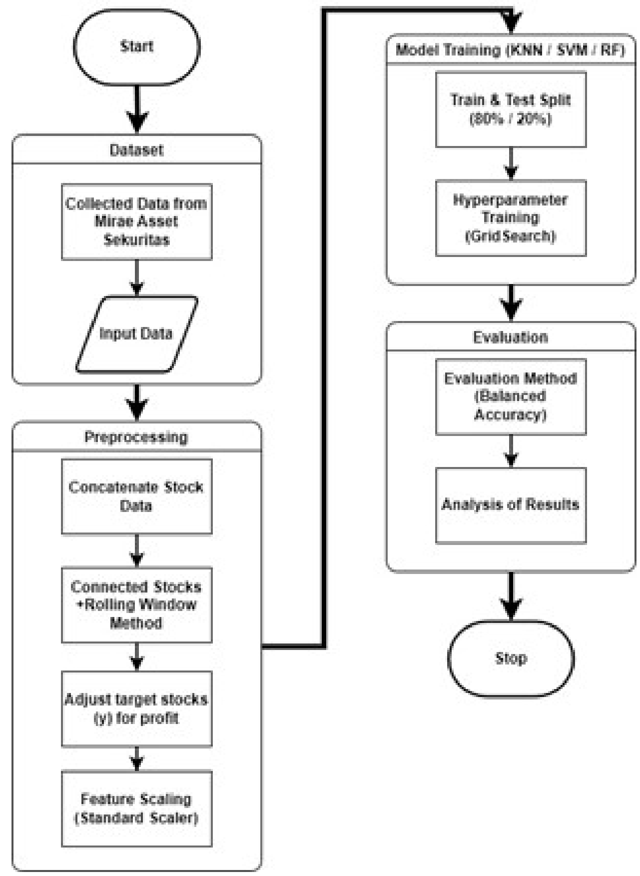


Figure 4. Main Research Framework

IDX is volatile [10], closely related [13], and less affected by foreign stocks [12]. All of this leads to our method where we use IDX's characteristics in regard to its interconnected stocks to predict the next day's high prices using machine learning techniques that we have found to work efficiently.

## 3. METHODOLOGY

In Methodology, there will be explanations in-depth regarding how the model is created through the framework in Fig. 4, while also illuminating the novel method that we are proposing by using historical stock data in the IDX and the interconnected stocks as the main theory.

### A. Data Collection

The dataset for this stock prediction came from Mirae Asset Sekuritas's software called HOTS30 which stores historical stock prices with features in IDX. We used several stocks that had a maximum total of 600 days in the stock market. The time period for these stocks starts at most from 8/9/2021 until 1/22/2024.

We stored several features alongside the basic features that HOTS30 provides at the beginning (Open, Low, High, Close, Volume) for further experimentation regarding how features impact the result of the model. After that, as

TABLE I. COMPARISON BETWEEN DIFFERENT STOCK EXCHANGES'S STOCK MARKET INDEX

| | IDX | Nasdaq | DJIA | Nikkei 225 | DAX |
|---|---|---|---|---|---|
| **Stock Count** | 911 | 3,418 | 30 | 225 | 40 |
| **Price** | 7,235.15 | 15,756.65 | 38,677.36 | 36,738.42 | 16,921.96 |
| **Total Sector** | 11 | 11 | 9 | 36 | 10 |

Figure 5. HOTS30 Dashboard

TABLE II. A SIMPLIFIED RESULT OF A STOCK EXTRACTION

| Date | Open | High | Low | Close | Volume |
|---|---|---|---|---|---|
| 1/22/2024 | 1,645 | 1,650 | 1,645 | 1,645 | 42 |
| 1/19/2024 | 1,670 | 1,705 | 1,640 | 1,645 | 1,382,762 |
| 1/18/2024 | 1,605 | 1,635 | 1,600 | 1,620 | 427,918 |
| 1/17/2024 | 1,620 | 1,620 | 1,600 | 1,605 | 223,405 |
| 1/16/2024 | 1,610 | 1,625 | 1,600 | 1,605 | 286,909 |

shown in Fig. 5, we extracted these features: Open, Low, High, Close, Moving Average (Price and Volume), Bollinger Bands, Weighted Close, Volume, PDI, MDI, ATR, Roc, and RSI.

Table II. showcases an example of the five first indexes in the ANTM stock and its features. The data provided by Mirae Asset Sekuritas gave us the main four basic features which are Open, High, Low, and Close. Open and Close both refer to the opening and closing price of the stock during the trading day, while High and Low both refer to the highest and lowest price of the stock during the trading day. There are also other features that we extracted as mentioned before. However, this is meant to be a simplified example of the input data that we got from HOTS30.

### *B. Pre-Processing*

According to Fig. 4, pre-processing will be extended into three different techniques, however before that, we will need to input the stocks data first as x. For every single stock that is used as an input and the features that are also used as an input, they will be put into a 1-D array together. As an example, the baseline model for this study will consist of four stocks: ANTM, ERAA, KLBF, and MIKA in which the baseline model also only uses a single feature which is 'Close'. Therefore, x consists of the closes from ANTM, ERAA, KLBF, and MIKA. After the pre-processed x has correctly been integrated, we proceed to the three stages of pre-processing.

#### *1) Connected Stocks + Rolling Window Method*

To grasp the inter-connected stocks in the IDX, we will be using a novel method combining the "Connected Stocks Method" and the "Rolling Window Method". By ensuring that the input (x) consists of the historical timeframe of each stock by using the rolling window while also consisting of multiple stocks at the same time, x will leverage the historical data and capture the temporal and inter-connected stock dynamics.

The "Connected Stocks Method" is inherently a simple method that means x will have sequential stocks between one another in the input. This can clearly be seen in Fig. 6, where in both forms the rolling window subsample has two connected stocks which are stock A and stock B. This means for example that if the input consists of two stocks A and B, while also consisting of two features 'Open' and 'Close' the ordered array of x would be the same as the array form in Fig. 6. This method's main usage is to capture the inter-connected stock dynamics to see if the stocks influence each other.

To capture the temporal dynamics of the Indonesian stock market, we decided to use the rolling window method. As seen in Fig. 7, this method captures a subset of the timeframe from the whole duration which will all be combined to capture the changes in the movement of the stock market, where the size of the window is how many days you want to capture in a window (portrayed in the graph form in Fig. 6). This means we need to store an additional variable that captures the subset turning the input into a 2-D array. Further examination of this can be seen in Fig. 7, where the rolling window method is already combined with the connected stocks method and forms a 2-D array that adjusts to both the data size and window size.

#### *2) Adjust Target stocks (y) for profit*

Since the main benefit of stock prediction is the profitability obtained from it, there needs to be a target that can achieve that benefit. For this research, we decided to predict a variable y, where it performs a binary classification of whether the next day's high is higher than 1.5% of today's close or not. Based on (1), we can calculate t which is the threshold. Once we have the value of t, we can then properly do a binary classification which is shown in (2).

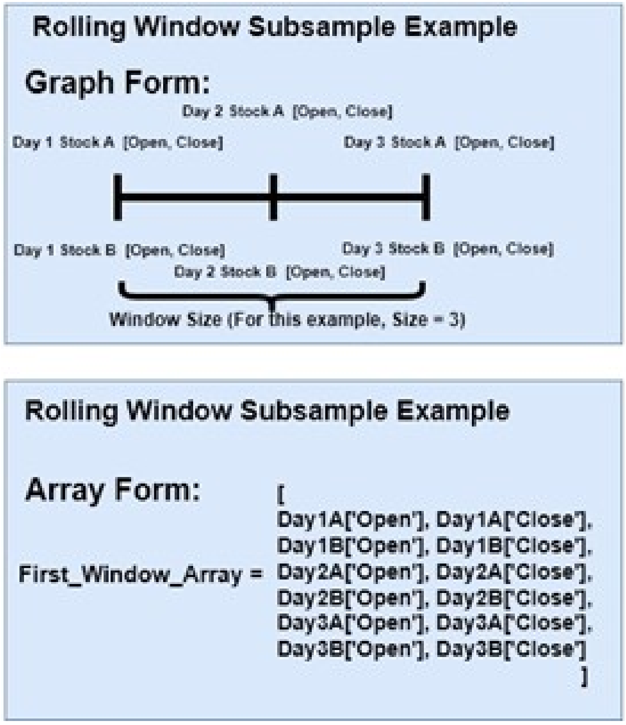


Figure 6. Rolling Window Subsample

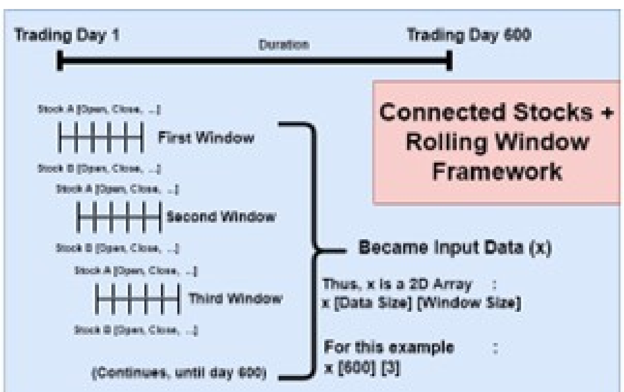


Figure 7. Connected Stocks + Rolling Window Framework

$$t = \frac{nexthigh - currentclose}{currentclose} * 100 \tag{1}$$

$$y = \begin{cases} 1 & if t \geq 1.5 \\ 0 & if t < 1.5 \end{cases} \tag{2}$$

The reason that we wanted t to be higher than 1.5% is because we wanted to account for the buy and sell fee provided by Mirae Asset Sekuritas [37]. The buy fee provided by them is 0.15%, while their sell fee is 0.25%. Both fees combined resulted in 0.4%, which means by subtraction we will get a profit of 1.1%. We would achieve our goal to try to earn a profit of a minimum of 1% every day.

*3) Feature scaling*

Feature scaling is crucial to employ standardization and ensure all features contribute equally to the model. For this model, we decided on using Standard Scaler since it preserves the shape of the original distribution, which is better for KNN and SVM, while RF is relatively unaffected by scaling since it is a tree-based algorithm. So, we standardized all our input of x based on (3) where $\mu$ refers to the mean of x and $\sigma$ refers to the standard deviation of x.

$$x_{standarized} = \frac{x - \mu}{\sigma} \tag{3}$$

## C. Train Test Split

We performed a train test split, with the split being 80/20, meaning 80% of it is training data, meanwhile 20% of it is test data. Since we used train_test_split as a function from sklearn, we also implemented a random_state to ensure that our results are replicable. Each stock has a data size of 600, meaning that we separate them into 480 training data and 120 test data. With this in mind, we will mostly experiment using four to five stocks to predict, which in total is around 2400 - 3000 data size, which is a good enough sample size for common machine learning models to learn the data.

## D. Hyperparameter Training and Model Training (KNN, SVM, RF)

From previous chapters, we learned that an optimal hyperparameter can boost the performance of the model highly [20], [38]. Because of this, we are doing hyperparameter tuning with grid search, a simple technique that evaluates a model's performance for each combination of hyperparameters in a grid. Since there are three machine learning models that we use, that means we have three different parameters for each grid which can be seen in Fig. 8. After proper hyperparameter tuning, each model can be trained according to hyperparameters from hyperparameter tuning.

## E. Model Evaluation

After the model is successfully trained, we can now evaluate the model's capabilities. For this model evaluation metric, we will be using balanced_accuracy_score from sklearn in which the mathematical model can be seen in (6). In that equation, sensitivity means the percentage of positive cases the model is able to detect, while specificity means the percentage of negative cases the model is able to detect.

After training the model, we assess its performance using a specific evaluation metric: balanced accuracy score from sklearn. Balanced accuracy considers two variables which are Sensitivity and Specificity. Sensitivity in (4) and Specificity in (5) measure the opposite of each other which

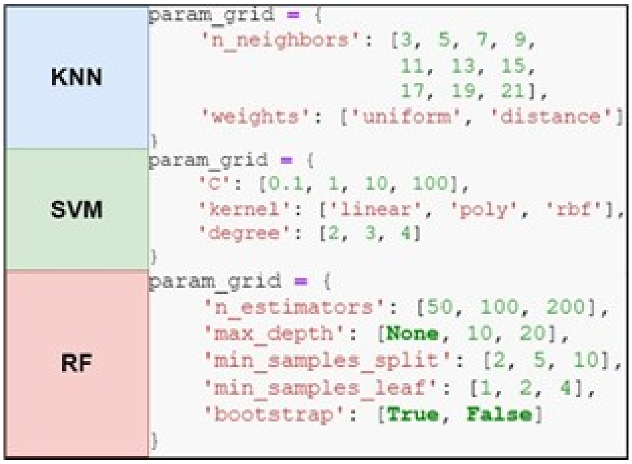


Figure 8. Parameters for each model

balances it out for balanced accuracy. Sensitivity refers to a true positive rate, calculating the proportion of true positives identified by the classifier, while specificity refers to a true negative rate, calculating the proportion of true negatives identified by the classifier.

$$Sensitivity = \frac{TP(TruePositive))}{TP(TruePositive) + FN(FalseNegative)} \tag{4}$$

$$Specificity = \frac{TN(TrueNegative))}{TN(TrueNegative) + FP(FalsePositive)} \tag{5}$$

$$BalancedAccuracy = \frac{Sensitivity + Specificity}{2} \tag{6}$$

When training the model, we found that generally most of the data and results tend to be skewed showing a class imbalance problem. When a model has shown an imbalance class problem, the evaluation method cannot purely be by accuracy since the results would be skewed [39]. Because of that, to ensure that the data is accurately representing the model's performance we decided to use Balanced Accuracy (6).

In regard to evaluating the model itself, we found that 55% is a good benchmark being a good result that shows stock connectivity, meanwhile, anything below that especially in the range of 50% or below shows that the stocks are not impacted by other stocks.

## 4. EXPERIMENT AND TASKS

### A. Experiment Setup

The experiments were performed on a computer with an Intel(R) Core (TM) i7-10750H CPU @ 2.60GHz, 8GB of RAM, and an NVIDIA GeForce GTX 1650 GPU. Python programming language (version 3.9.7) was the main programming language used to train our models. Libraries such as NumPy, Pandas, and Scikit-learn were used for data collection, data preprocessing, train-test split, hyperparameter tuning, and model evaluation. All experiments were conducted within a Jupyter Notebook environment.

### B. Experimented Stocks

In Table III, we included all stocks that we experimented on. Most of the stocks in the list are from either the basic materials or financials sector. This is because several stocks within the same sector will be tested as parameters in our experiments. We also calculated their last known total sale, which is in Q3 2023, where most of these stocks have a similar range.

### C. Description of Tasks

To obtain a comprehensive understanding of the dynamics of the interconnected stocks in IDX, we performed multiple experiments that focus on different aspects of the training, starting from pre-processing where we test a variety of inputs, experiment using different features and its data size, experiment using model and stocks that has a balanced classification target data, consider using different window sizes, and consider sector-specific stock interconnection. By properly investigating IDX's stocks we will have a better understanding of how our method properly predicts stock prices.

#### 1) Baseline Model

Since the training data that we use are not similar to other relevant papers in this field, we created a baseline model that will be the base of comparison for every other experiment. All other models will share identical parameters with this baseline (window size, stock selection, features, etc.), except for one variable, which will be the target for experimental comparison purposes.

The baseline model's input stocks are ANTM, ERAA, KLBF, and MIKA, using only the 'Close' feature as input. This means the input (x) for the baseline model includes the closing prices of these four stocks. For the novel connected stocks + rolling window method, we use the window size of four. The evaluation method for the baseline model and every other experiment will be the one discussed in Section 3 which is a balanced accuracy metric.

#### 2) Testing using Different Features

Commonly, additional features as inputs help machine learning models improve their performance therefore there needs to be an experiment to show if it is true for this case. We created two additional models using two different features, which can be seen in Table IV. Models with common features will have five input features and are supposed to represent standard stock prediction models that only use the basic features. Advanced features include technical indicators into the mix which should help increase the model's performance. For advanced features, in total, they have 29 input features.

TABLE III. LISTS OF STOCKS EXPERIMENTED

| Stock Name | Company | Sector | Total Sales Q3 2023 (in Rupiah) |
|---|---|---|---|
| **ANTM** | Aneka Tambang Tbk | Basic Materials | 30.898T |
| **ERAA** | Erajaya Swasembada Tbk | Consumer Cyclicals | 42.816T |
| **KLBF** | Kalbe Farma Tbk | Healthcare | 22.561T |
| **MIKA** | Mitra Keluarga Karyasehat Tbk | Healthcare | 3.156T |
| **DUTI** | Duta Pertiwi Tbk. | Properties and Real Estate | 2.903T |
| **DSSA** | Dian Swastatika Sentosa Tbk | Energy | 5.782T |
| **ARTO** | Bank Jago Tbk | Financials | 0.8T |
| **BBRI** | Bank Rakyat Indonesia (Persero) | Financials | 31.603T |
| **BBTN** | Bank Tabungan Negara (Persero) | Financials | 1.426T |
| **BFIN** | BFI Finance Indonesia Tbk. | Financials | 2.056T |
| **BNGA** | Bank CIMB Niaga Tbk. | Financials | 3.896T |
| **BRPT** | Barito Pacific Tbk. | Basic Materials | 18.617T |
| **CMNT** | Cemindo Gemilang Tbk. | Basic Materials | 0.434T |
| **MDKA** | Merdeka Copper Gold Tbk. | Basic Materials | 6.689T |
| **TPIA** | Chandra Asri Pacific Tbk. | Basic Materials | 12.783T |

TABLE IV. COMPARISON USING DIFFERENT FEATURES

| Name | Features Used |
|---|---|
| **Baseline Features** | Close |
| **Common Features** | Open, High, Low, Close, Volume |
| **Advanced Features** | Open, Low, High, Close, Volume, Moving Average (Price and Volume), Bollinger Bands, Weighted Close, PDI, MDI, ATR, Roc, and RSI |

*3) Testing Using a Balanced Threshold Model*

In prior testing, particularly with SVM, we observed a tendency for one-sided predictions where every stock was forecasted to be either higher or lower than the threshold. These results suggest an imbalanced data classification. While we cannot adjust our threshold model in our target stock (y) to guarantee a minimum 1% profit, we can explore what would happen if each stock had a more balanced target. This approach could mitigate the imbalance issue in the data.

Barkah et al. [40] described in detail the impact of having an imbalanced data in machine learning. An imbalanced data creates models that have a deeper understanding of the majority in classes compared to the minority, creating biases, which can overfit the model. Consequently, having a balanced dataset is crucial in any machine learning model, and therefore we are testing whether a balanced threshold model will reduce bias in our model during learning.

As you can see in Table V, we have adjusted the threshold for every single stock in the baseline model to be balanced. This means every single stock has a perfectly balanced data classification by adjusting the threshold to fit those criteria. From the table, you can see that every threshold when balanced is still positive, showing that every single stock's growth has in the majority been positive.

TABLE V. LISTS OF BALANCED THRESHOLD FOR EACH STOCK

| Name | Threshold(t) |
|---|---|
| Original Threshold | 1.5 |
| ANTM's Balanced Threshold | 1.2 |
| ERAA's Balanced Threshold | 1.265 |
| KLBF's Balanced Threshold | 0.93 |
| MIKA's Balanced Threshold | 1.535 |

*4) Testing Using Different Window Size*

Window size is a variable used in the rolling window method to assess the performance of a model in a particle timeframe. By exploring the effect of different window sizes, we can see whether it affects the model's performance. For this experiment, we decided to test these window sizes: 5, 10, 15, 20, and 60 days. Since we are trying to compare different window sizes, this means that the stock that we use as a comparison must be the same. Instead of using one of the stocks as a comparison, we use the average result of each stock as a comparison. This ensures the model's generalizability and that the result won't be skewed by a specific stock's permeability to a window size.

*5) Testing Using Different Stock Size*

Normally, increasing the amount of input data to the model will increase the model's performance. However, in

TABLE VI. LIST OF DIFFERENT STOCK SIZE EXPERIMENTS

| Stock Lists | Number of Stocks |
|---|---|
| [ANTM, ERAA, KLBF] | 3 |
| [ANTM, ERAA, KLBF, MIKA] | 4 |
| [ANTM, ERAA, KLBF, MIKA, DUTI] | 5 |
| [ANTM, ERAA, KLBF, MIKA, DUTI, DSSA] | 6 |

the case of our model, since the input data also considers interconnectivity between stocks there's a chance that adding more stocks reduces the probability of the stocks influencing each other, thus lowering the model's performance. Because of this, we are going to experiment with different stock sizes as inputs which the list is shown in Table VI.

Like our experiment with different window sizes, the target that we are trying to compare is between stock sizes, meaning we must use the same stock as a comparison. Instead of using one of the stocks as a comparison, we use the average result of each stock as a comparison. The stocks that we use as the predicted stocks will be ANTM, ERAA, and KLBF since we need to experiment with the results on a model that has three as its stock size. The model will follow the structure of the baseline model, other than the input it uses.

*6) Testing Using a Specific Sector (Financial Sector)*

In IDX, stocks are grouped into various sectors such as Healthcare, Financials, and others. Since our baseline model is composed of stocks from different sectors, we want to compare that to models that are purely trained using a specific sector. For this experiment, we will be using the Financial Sector as the specific sector using ARTO, BBRI, BBTN, BFIN, and BNGA as the input and target stocks.

*7) Testing Using a Combination of Specific Sectors (Basic Materials Sector)*

Similar to the prior experiment, this one will analyze a group of stocks from the same sector, the Basic Materials Sector. We will use BRPT, CMNT, MDKA, and TPIA as input and target stocks. Unlike before, we will also merge the Basic Materials and Financials sectors as input stocks. The aim is to assess if combining sectors as input data improves the model's performance in predicting Basic Materials stocks. This means BRPT, CMNT, MDKA, TPIA, ARTO, BBRI, BBTN, BFIN, and BNGA will serve as input stocks.

## 5. RESULTS AND DISCUSSION

In this section, we will be going over the results from the experimentation explained in the previous section. We will add another model which is the average of all the other Machine Learning models (KNN, SVM, RF) to better judge how each stock's interconnectivity truly is. The results

TABLE VII. ACCURACY RESULTS USING BASELINE MODEL

| Machine Learning Model | Stock Name ANTM | ERAA | KLBF | MIKA |
|---|---|---|---|---|
| KNN | **0.6054** | 0.5979 | 0.5099 | 0.4742 |
| SVM | 0.5439 | **0.5626** | 0.5 | 0.5508 |
| RF | 0.5403 | **0.614** | 0.516 | 0.5646 |
| Average | 0.5632 | **0.5915** | 0.5086 | 0.5298 |

TABLE VIII. ACCURACY COMPARISON USING DIFFERENT FEATURES

| Features | Machine Learning Model | Stock Name ANTM | ERAA | KLBF | MIKA |
|---|---|---|---|---|---|
| Common Features | KNN | 0.5615 | **0.6394** | 0.4996 | 0.5492 |
| | SVM | 0.5425 | **0.6121** | 0.4521 | 0.5319 |
| | RF | 0.5294 | **0.614** | 0.5028 | 0.5457 |
| | Average | 0.5445 | **0.6218** | 0.4849 | 0.5423 |
| Advanced Features | KNN | **0.5952** | 0.5809 | 0.5221 | 0.5473 |
| | SVM | 0.5709 | **0.5973** | 0.4878 | 0.5696 |
| | RF | **0.6424** | 0.5821 | 0.4906 | 0.5909 |
| | Average | **0.6029** | 0.5868 | 0.5002 | 0.5693 |

from the table will follow our evaluation metric, balanced accuracy score. According to our evaluation method, if a stock is classified as having high interconnectivity, then it should at minimum be $> 55\%$. If any stock has an evaluation score that is $\leq 50\%$, it means that they are not connected at all.

### *A. Testing Results Using Baseline Model*

It can be seen from Table VII, that the baseline model performed well for ANTM and ERAA, reaching an average accuracy of 56% and 59% respectively. However, for KLBF and MIKA this isn't the case, only reaching 50% and 52% respectively. While MIKA performed terribly using KNN, it performed well using the others showing that the stock might be interconnected and KNN is just an outlier KLBF however is definitely not connected having consistently terrible performance on every model. Comparatively from each machine learning model, RF showcased the best performance against each model where only KLBF was inaccurately predicted.

### *B. Testing Results Using Common Features and Advanced Features*

From the comparison Table VIII, it is found that additional features don't give consistent improvement to most stock's performance except MIKA. ANTM on average performed best when using advanced features, but ERAA on average performed best when using common features showing that it is an indecisive proof. KLBF has shown itself as a stock that is not interconnected since it has consistently performed around 50% accuracy. MIKA however performed well compared to the baseline model, showing that it might be an interconnected stock that was trained badly by KNN on the baseline model. Regarding the algorithm itself, all three models performed well except at KLBF where RF performed the best with a slight edge.

TABLE IX. ACCURACY RESULT USING BASELINE MODEL WITH BALANCED THRESHOLD

| Machine Learning Model | Stock Name ANTM | ERAA | KLBF | MIKA |
|---|---|---|---|---|
| KNN | **0.5797** | 0.5691 | 0.5781 | 0.4856 |
| SVM | 0.5517 | **0.5982** | 0.5204 | 0.5567 |
| RF | 0.5258 | 0.5703 | **0.6562** | 0.5944 |
| Average | 0.5524 | 0.5792 | **0.5849** | 0.5456 |

### *C. Testing Results Using Balanced Threshold Model*

From Table IX, it is found that the model that uses a balanced threshold significantly improved the performance of each stock that was not interconnected yet. While ANTM and ERAA still performed well similarly as a stock, KLBF and MIKA found massive improvement as a target stock. KLBF performed the best out of everyone achieving an average accuracy of 58%, massively improving and showing interconnectedness when compared to previous results. MIKA also performed well, achieving an average of 54% accuracy, where its average is badly influenced because of sudden KNN drop-off which is the main reason why its average is under 55%. From the machine learning perspective, RF as usual performed the best out of all the machine learning models. SVM performed consistently well achieving results mostly above the threshold of 55% except at KLBF, and KNN seems to perform well but with random failed results at capturing interconnectivity in stocks such as MIKA in Table VIII.

### *D. Testing Results with Different Window Size*

Analyzing the stock comparison in Fig. 9-12, ANTM did not perform well when the window size is between 10-20. ERAA as usual performed well under any experiments achieving an average higher than 55% on every single window size. KLBF performed consistently awful, except when window size is 10 due to KNN randomly performing well which now seems to be consistent as a trait for KNN. MIKA had a good performance, in which the model started to improve when the window size was 15 and improved further. From the machine learning perspective, RF performed the best as usual, however, it is strange to see SVM perform the worst at stocks like ANTM. KNN as usual has a good performance with slightly random results.

Analyzing Table X, it can be seen that the previous analysis is reflected in the table. With ANTM performing worse and MIKA performing better than normal it evens out when averaged. Other than these two, ERAA and KLBF remained consistent, meaning that when the stocks are averaged the score is relatively the same. There does not seem to be a pattern found in Table X, where the accuracy fluctuates with increased window size, suggesting that different window sizes don't affect the performance of the model. This is even further shown through different machine learning models, where they remained stagnant with only tiny differences.

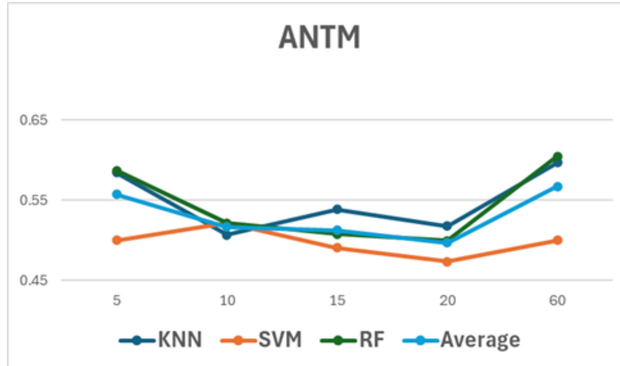


Figure 9. ANTM Comparison on Results with Different Window Size

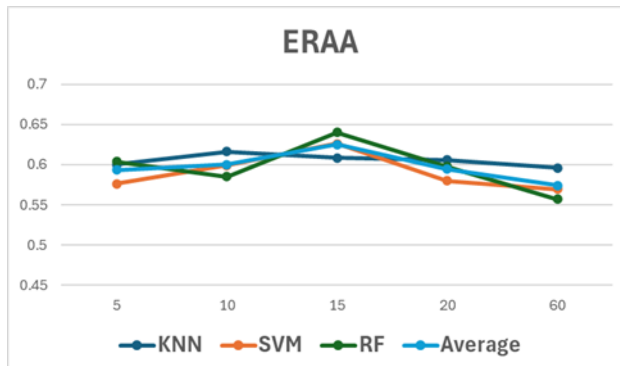


Figure 10. ERAA Comparison on Results with Different Window Size

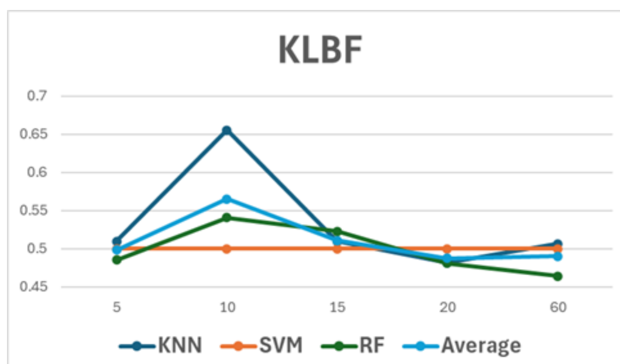


Figure 11. KLBF Comparison on Results with Different Window Size

TABLE X. ACCURACY RESULT USING BASELINE MODEL WITH DIFFERENT WINDOW FOR AVERAGE STOCKS

| Machine Learning Model | Window Size 5 | 10 | 15 | 20 | 60 |
|---|---|---|---|---|---|
| KNN | 0.5622 | **0.5677** | 0.5646 | 0.5315 | 0.57 |
| SVM | 0.5277 | 0.5417 | **0.544** | 0.54 | 0.5423 |
| RF | 0.5572 | 0.5488 | **0.5723** | 0.5356 | 0.5547 |
| Average | 0.549 | 0.5527 | **0.5603** | 0.5357 | 0.5556 |

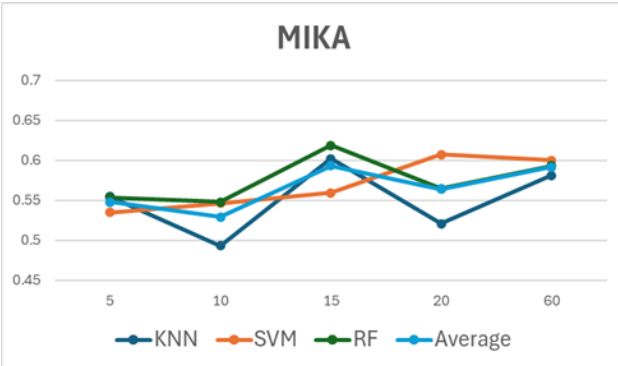


Figure 12. MIKA Comparison on Results with Different Window Size

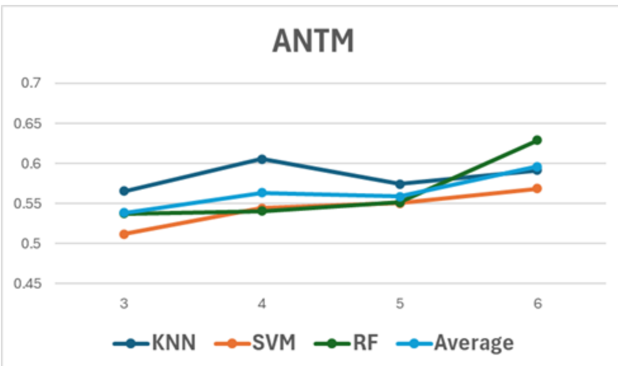


Figure 13. ANTM Comparison on Results with Different Stock Size

### E. *Testing Results with Different Stock Size*

Analyzing the stocks comparison in Fig. 13 - 15, ANTM performed consistently well where on average it improved and almost reached 60% when using six stocks as input data. ERAA performed consistently well, this time on average reaching around 60% accuracy. KLBF on average performed below the criteria as usual, however has shown improvement with additional stock size.

Analyzing Table XI, the previous stock comparison is

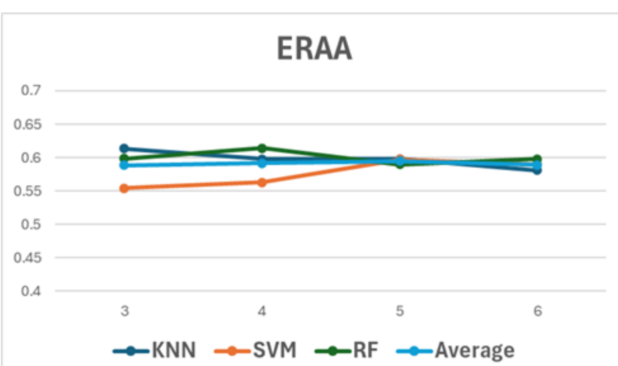


Figure 14. ERAA Comparison on Results with Different Stock Size

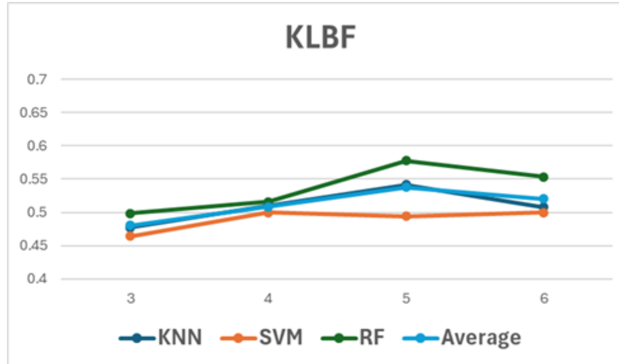


Figure 15. KLBF Comparison on Results with Different Stock Size

TABLE XI. ACCURACY RESULT USING BASELINE MODEL WITH DIFFERENT STOCK SIZE FOR AVERAGE STOCKS

| **Machine Learning Model** | **Stock Size 3** | **4** | **5** | **6** |
|---|---|---|---|---|
| KNN | 0.5521 | **0.5711** | **0.5711** | 0.56 |
| SVM | 0.51 | 0.5355 | **0.5471** | 0.5526 |
| RF | 0.5447 | 0.5568 | 0.5729 | **0.5934** |
| Average | 0.5356 | 0.5545 | 0.5637 | **0.5687** |

reflected in this table showcasing growth. On average, the performance of the model increases as the stock size as input increases, giving a new insight on improving the model. Looking at the machine learning models themselves, RF and KNN performed well, while SVM did not perform as well when the stock size was small meaning it adapts better to bigger datasets.

### F. *Testing Results in a Specific Sector (Financial Sector)*

Looking at Table XII, we can see each result of stocks in the financial sector. All five models performed terribly and not even one hit the benchmark of 55% accuracy on average. Other than that, machine learning models also performed consistently terribly except for RF achieving two models above the benchmark. This table shows that using specific sectors as input might ruin the interconnectivity of the stocks as they are volatile with each other, and that RF is the best machine learning model so far compared between the three.

TABLE XII. ACCURACY RESULT USING FINANCIAL SECTOR MODEL

| **Machine Learning Model** | **Stock Name ARTO** | **BBRI** | **BBTN** | **BFIN** | **BNGA** |
|---|---|---|---|---|---|
| KNN | 0.527 | 0.5135 | 0.4921 | **0.5537** | 0.5146 |
| SVM | 0.4908 | 0.5 | 0.5154 | **0.5184** | 0.5 |
| RF | **0.5889** | 0.4939 | 0.5205 | 0.5337 | 0.563 |
| Average | **0.5355** | 0.5024 | 0.5093 | 0.5353 | 0.5259 |

TABLE XIII. ACCURACY COMPARISONS BETWEEN SPECIFIC SECTORS AND JOINT SECTORS

| Stock Input | Machine Learning Model | BRPT | CMNT | MDKA | TPIA |
|---|---|---|---|---|---|
| Basic Materials Sector Input | KNN | **0.6293** | 0.5458 | 0.4893 | 0.5124 |
| | SVM | **0.6693** | 0.4939 | 0.464 | 0.5377 |
| | RF | **0.603** | 0.5248 | 0.5429 | 0.5699 |
| | Average | **0.6339** | 0.5215 | 0.4988 | 0.54 |
| Combined Sector Input (Basic Material + Financial) | KNN | **0.6556** | 0.5489 | 0.4878 | 0.493 |
| | SVM | **0.6793** | 0.5609 | 0.5309 | 0.4933 |
| | RF | **0.6889** | 0.4945 | 0.464 | 0.5695 |
| | Average | **0.6746** | 0.5348 | 0.4943 | 0.5186 |

### *G. Testing Results in a Specific Sector and Combined Sector Models (Basic Material Sector)*

Looking at Table XIII, it can be seen that on average the model mostly improved with additional stock inputs similar to Table XI. However, similar to Table XII as well, models trained using specific sectors have shown terrible performance with the exception of BRPT. When looking at the machine learning model, SVM and RF performed better with additional inputs, while KNN performed similarly through both comparisons. The table showcases that while there might be stocks like BRPT that are interconnected when trained using specific sectors achieving accuracy as high as 67%, generally the model will perform worse and not achieve the benchmark.

### *H. Summary of Testing Results*

Implementing the novel method "Connected Stocks + Rolling Window Method" on several machine learning models with several experimentations has resulted in several interesting discoveries. Regarding the baseline stocks, ANTM and MIKA have shown improvement with additional help through features, balanced datasets, etc. ANTM and ERAA performed well, with ERAA consistently performing well in any experiment. KLBF performed the worst where it lacks change, showing it is not interconnected, however with proper balancing data it has been shown that this stock can perform well. Here are several key points to summarize the test results:

- Implementing additional features did not impact the model's performance in a positive way, only causing fluctuations of accuracy for each model and stock (except for MIKA).
- The balanced threshold model proved to significantly improve each stock's performance, proving the importance of having a balanced class of data.
- The differences in window size during the experiment did not impact the model's accuracy in any meaningful way.
- Increased stock size was able to improve the model's performance on average.
- Using specific sectors, instead of a variety of stocks, did not improve the model, even shown to be worse where almost all of them did not hit the minimum benchmark of 55%.
- Combining input data from sectors might help improve the model for stocks that are interconnected like BRPT, however, it was not able to help stocks that were not.

## 6. CONCLUSION

To deal with the volatility of the IDX, we examined the stocks's interconnectedness using our novel method "Connected Stocks + Rolling Window Method" to predict the next day's high of stocks in IDX using several machine learning models (KNN, SVM, RF). We found that having balanced classification data improved the model's performance significantly. Using a higher amount of input stocks also improved the accuracy, especially interconnected stocks. The machine learning model that performed the best was found to be Random Forest. In the end, we successfully showed the effects of interconnectedness in the IDX and were able to predict the next day's high using several stocks including ANTM, ERAA, and BRPT having accuracies higher than 55% most of the time through the use of the stock's interconnectedness.

This study is limited to the stocks used in the Indonesian Stock Exchange. It uses several stocks from the IDX in the time period from 8/9/2021 until 1/22/2024 where we analyzed and predict the model using different machine learning models. Due to this, the research still provides a number of avenues that may be taken into account in order to conduct future research, which may lead to a variety of directions. Exploring the usage of deep learning techniques instead of traditional machine learning could help improve the model. Deep learning has a weakness in the world of stock prediction, where it is noticeably slower compared to machine learning, however, an optimized model with better performance and reasonable speed can be beneficial. Further research into testing the model on other stock exchanges may help show its generalizability. While the reasoning behind the research is due to IDX's characteristics, experimenting on other exchanges will give insight into the model's characteristics. The other main issue that future research could address is the imbalanced data problem. Our results showed that having balanced data helps improve each stock's performance significantly. Therefore, implementing techniques to handle imbalanced datasets to achieve results similar to balanced datasets could help improve the model's performance without having to adjust its threshold.

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