Classification of Stock Price Movements Using Multilayer Perceptron with Trend, Momentum, and Volume Indicators

ABSTRACT

Stock trading focuses on leveraging fluctuations in stock prices to make a profit. Trading strategies are developed to help determine the right moment to buy and sell stocks in the market. These strategies can be built manually through fundamental, technical, and sentiment analysis, or using Machine Learning techniques that process historical stock data to generate buy and sell signals, enabling easier decision-making. This research proposes a Machine Learning model using the Multilayer Perceptron Backpropagation algorithm with four layers, which utilizes technical indicators as features. The model uses seven main features, namely: momentum value, Price Oscillator, difference between On-Balance Volume (OBV) value and the average OBV of the preceding five days, change in distance between price and Moving Average (MA) 10, distance between Relative Strength Index (RSI) value and MA10 (RSI), change in distance between MA20 and MA50, and difference between %K and %D of Stochastic indicator. The classification categories are divided into three classes, namely: Buy, Sell, and Hold. The historical data used includes closing price and volume for 10 years, from January 1, 2014 to December 31, 2023, taken from Yahoo! Finance. The model is optimized using a Risk-Reward Ratio of 1:2, with a profit target of 6% and a loss limit of 3%, and an evaluation period of 10 days. Model testing was conducted on ASII, TLKM, PWON, BBRI, BBCA, BNGA, UNVR, GGRM, and HMSP stocks, which represent categories of stocks with sideways, uptrend, and downtrend trends. The test results provide an average accuracy rate of 65%, with the greatest accuracy in BBCA stock at 75%, and the smallest accuracy in PWON stock at 57%. From the confusion matrix, the average win-loss ratio value is 5.23 times. This indicates that the success rate of transactions that generate profits is 5 times that of transactions that generate losses.

***Keywords**:* stock price, stock trading, machine learning, technical indicators.

INTRODUCTION

Making a profit in the stock market can be achieved through investing and trading. The focus of investment is generally on buying certain stocks from companies with good fundamental performance and future prospects, that are still priced below their intrinsic price. Making profits through trading focuses on gaining profits by capitalizing on fluctuations in stock prices by buying shares at a certain price and selling them at a higher price to benefit from the difference between the selling price and the buying price. To increase the percentage of profit and minimize risk, it is necessary to create a good trading strategy. A trading strategy is a method to help determine the right time to buy and sell stocks in the market. Trading strategies can be created using fundamental analysis, technical analysis, or sentiment analysis. These strategies can be created manually or by utilizing computer algorithms through artificial intelligence and machine learning. Machine learning algorithms will process historical stock data to help generate buy and sell signals, which will help make trading decisions easier.

Machine learning algorithms can be developed to create trading strategies. Machine learning has the ability to process large-scale and complex data in a significantly faster time than using ordinary manual analysis or ordinary technical analysis. Machine learning algorithms can be used to identify certain patterns from large data sets that may not be visible manually or using ordinary technical tools. In the stock trading domain, machine learning algorithms perform price prediction similar to using regression analysis, or by classifying signals to buy, sell, or hold. This research proposes a Machine Learning model using the Multilayer Perceptron Backpropagation algorithm with four layers, which utilizes technical indicators as input features. The historical data used in this research is taken from Yahoo! Finance with Daily time frames spanning from January 1, 2014 to December 31, 2023 or for 10 years.

LITEATURE REVIEW

Multilayer Perceptron

A basic kind of artificial neural network, the multilayer perceptron (MLP) has been extensively employed for various kinds of tasks, such as regression and classification. An MLP is made up of three layers: an input layer, one or more hidden layers, and an output layer. Each layer is made up of neurons that use activation functions and weighted connections to interpret input signals. MLPs' architecture enables them to use hyperplanes to divide the input feature space into several subspaces, making it easier to classify data into discrete groups. Because of this feature, MLPs are especially effective at handling complicated issues that are not linearly separable (Zhang, Lipton, Li, & Smola, 2023).
An example of a basic MLP structure is illustrated in Figure 1. The basic structure includes an input layer, one or more hidden layers, and an output layer. The input layer receives the initial data. Each neuron in this layer represents a feature of the input data. Hidden layers perform computation and extract features from the input data. Each neuron in a hidden layer applies a weighted sum of its inputs and passes the result through a nonlinear activation function. The output layer produces the final output of the network. The number of neurons in this layer corresponds to the number of the desired outputs.

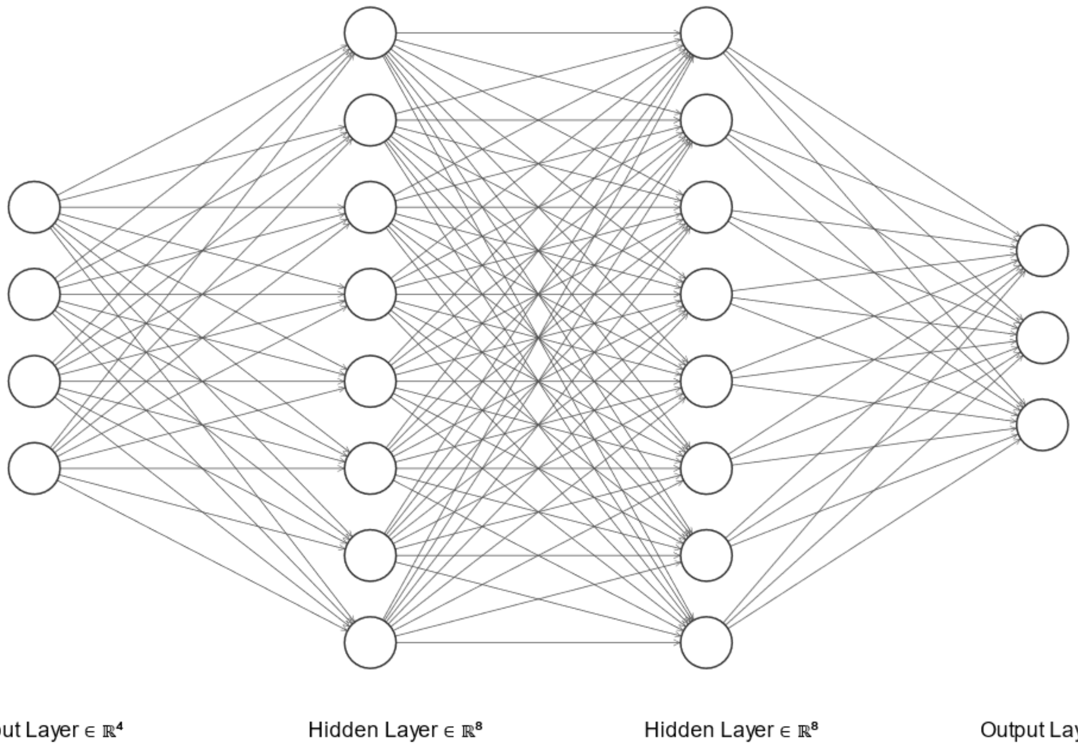

Figure 1.
Multilayer perceptron basic structure

The input layer can be represented by the matrix $X \in R^n$, consists of n neurons. For each hidden layer in MLP has h hidden units, denoted by $H \in R^h$ the outputs of the hidden layer. Since the input layer, hidden layer and output layer are both fully connected, the weight of the connection can be represented by the matrix $W \in R^{dh}$ and $W \in R^{hq}$. The biases used can be represented by the matrix $b \in R^n$ and $b \in R^h$. The output of the network (O) can be calculated as follows (Zhang, Lipton, Li, & Smola, 2023):

$$H^1 = XW^1 + b^1$$
$$H^2 = H^1W^2 + b^2$$
$$O = H^2W^2 + b^3$$

Nonlinearity can be implemented in the network by adding activation functions. Activation function decides the activation state of a neuron in the network. There are several commonly used activation functions such as Rectified Linear Unit (ReLU), Sigmoid, Tanh, and SoftMax. The output of the network (O) passed through the activation function are represented by $Output = ReLU(H^2W^2 + b^3)$.

Machine learning methods and deep learning algorithms can be used to predict stock prices. Machine learning models MLP (Multilayer Perceptrons) and LSTM (Long Short-Term Memory) provide better estimation reliability compared to the SVM (Support Vector Machines) model. The highest R-squared (R2) value at closing value was 0.978 in the LSTM model, while the lowest was 0.580 in the SVM model (Demirel, Cam, & Unlu, 2021). Machine Learning LSTM combined with technical indicators that have a correlation value of more than 0.3 provides better results than LSTM without technical indicator features (Hakim, Fariza, & Setiawardhana, 2023). Technical analysis indicators can be used as input features for the neural networks for intraday stocks predictions (Borovkova & Tsiamas, 2019). Rivero, et al. (2023) used artificial neural networks to predict the movement of several stocks on the Sao Paulo Stock exchange using weekly time frame with research data for one year. Neural networks architecture created using an input layer, two hidden layers, and an output layer with seven input data: high value, open value, close value, low value, close value adjusted, volume, and Moving Average 8. The results showed that ANN gave a good gain with an accuracy rate of 62.5%.

The theory of technical indicators and how to use them from the megaprofit book, technical indicators in the analysis of stock movements are used to detect trends or tendencies in the direction of stock prices and to read the momentum of a stock. Technical analysis provides information to investors or traders to help make decisions in stock trading. Technical analysis provides a visual representation of market behavior. Accurate and thorough technical analysis can help make risk management more measurable. (Ramadhani, Handayani, Sari, & Rizal, 2023). A combination of several technical indicators will give better results than a single indicator (Pramudya & Ichsani, 2020).

OBV Indicator- ON Balance Volume

OBV is an indicator that combines the price with the volume of a stock based on the total cumulative volume. If the price rises, then the volume on that day will be added, conversely if the price falls, then the volume on that day will be used to reduce the OBV value. (Ong, 2016). The formula of OBV is given below.

$$OBV = OBV_{prev} + \begin{cases} volume, if\ close > close_{prev} \\ 0, if\ close = close_{prev} \\ -volume, if\ \ close < close_{prev} \end{cases}$$

The OBV indicator is used to read the buying and selling pressure of a stock. Under normal conditions, the price movement will be in line with the movement of the OBV curve. If the OBV curve is in the opposite direction to the trend, it can signal the possibility that the trend will reverse. An example of the OBV Curve on PWON shares is given in Figure 2.

Figure 2.
OBV Indicator

Moving Average Indicator

Simple Moving Average/Moving Average (MA) is the average value of the closing price movement of a stock within a certain period, usually using the closing price. For example, the 5-day MA value is obtained by calculating the average of the last 5-day closing prices.

$$MA(n) = \frac{p_1 + p_2 + \cdots + p_n}{n}$$

The calculated values are displayed in the form of curves accompanying the charts. The MA indicator is commonly used as a trend indicator, if the stock price is above the MA curve, it is a bullish trend, otherwise if the price is below the MA curve, it is a bearish trend. (Ong, 2016).

Relative Strength Index (RSI)

RSI is a momentum indicator that measures speed and price changes. The formula for calculating RSI is given below.

$RSI = 100 - \left(\frac{100}{1+RS}\right)$, dengan

$$RS = \frac{average\ gain\ dalam\ n-day}{average\ loss\ dalam\ n-day}$$

RSI operates between a scale of 0 and 100. An RSI value that approaches 0 indicates a weakening of price momentum, conversely, an RSI that approaches 100 indicates a strengthening of price momentum. The MACD and RSI indicators can be used to analyze stock price movements (Hasan, Nurhasanah, & Santoso, 2024). Bullish Divergence on the MACD can indicate a bullish trend, while an RSI value that starts to rise above 50 signals the beginning of a forming bullish trend. (Yulianti & Kusuma, 2024). RSI values that are in an oversold condition, and the close stock price is outside the Lower Band of the Bollinger can indicate a buy signal on construction stocks (Firdaus, 2021), on tin and nickel commodity-based stocks (Setiadi, Putri , Ardilia, & Azmi, 2022), and major banking stocks (Akbar, 2024).

Price Oscillator Indicator (PPO)

PPO is a technical indicator used to measure stock price momentum. The PPO indicator is measured using the difference of two periods of Exponential Moving Average expressed in percent with the formula given below.

$$PPO\ Line = \frac{(EMA12 - EMA26)}{EMA26} x100$$

Signal Line = *EMA9*(*PPO Line*)

PPO Histogram = *PPO Line* – Signal Line

If the PPO histogram value is positive and rising, then there is upward momentum in prices, and vice versa.

Momentum

Momentum is an indicator to measure the speed of change in the price of a stock. If the line crosses the 0 (zero) line upwards it is a buy signal, otherwise if it crosses the zero line downwards it is a sell signal. The formula of Momentum is given by the following equation.

$M(n) = Cp_{today} - Cp(n - day)$,

with Cp_{today} = today closing price

Cp(*n-days*) = closing price n-day before

n= periode waktu yang digunakan.

A momentum line that is in the same direction as the stock price movement indicates that the trend is gaining momentum, otherwise if it is in the opposite direction, then the trend is starting to lose momentum (Ong, 2016).

Stochastics

The Stochastic indicator displays two lines in the oscillator called the %K line and the %D line with a value scale ranging from 0 - 100. The %K line is calculated using the percentage ratio between the last closing price and the highest and lowest price over a given period. The %D is calculated using a 3-day moving average of the %K. The intersection of the %K and %D lines from bottom to top on the stochastic indicator may indicate a buy signal (Sadikin & Agustina, 2023).

RESEARCH METHOD

This research was conducted by building a machine learning model using technical analysis features to classify stock prices. Figure 3 provides the methodological diagram applied in this research.

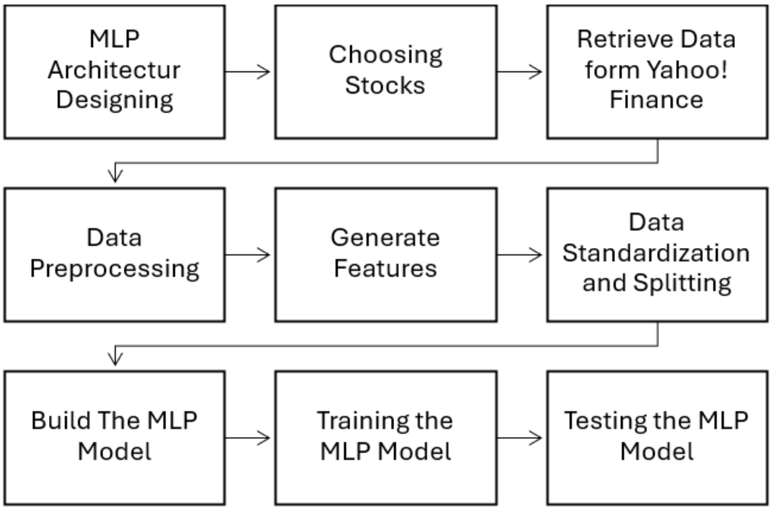

Figure 3.
Methodological Research Diagram

Retrieve Data from Yahoo! Finance

This research began by preparing data that would be used as input in building machine learning models with MLP neural networks algorithms. The historical data used in this study includes the closing price and volume of shares for 10 years, from January 1, 2014 to December 31, 2023, taken from Yahoo! Finance with a daily timeframe.

Data Preprocessing

The next step is to create additional columns containing the technical indicator values that will be used by the machine learning model. Rows containing NaN (Not a Number) values were removed from the historical data table. The existing data is labeled to divide it into three classes, namely: Buy, Hold, and Sell. Labeling is done automatically by the system by following the Risk-Reward Ratio 1:2 method, with a 10-day lookup period. The Target Reward given in this study is 0.06 or 6%, while the Target Loss is -0.03 or minus 3%. The formula for creating class labels is given below.

target_profit = 0.06
target_loss = -0.03
lookup_period = 10
Ratio of Close: $ROC = \frac{Close(next\ 10-day) - Close}{Close}$
if ROC >= target_profit, then Label = "Buy"
if ROC <= target_loss, then Label = "Sell"
else Label = "Hold"

Generate Features

In this study, the creation and selection of 7 features were carried out, namely:

- 1st feature: F1 = OBV – MA5(OBV).
  The purpose of selecting this feature is that the increase in OBV value compared to the previous value also reflects the increase in stock price, and vice versa. MA5(OBV) is used as a comparison for the OBV value, due to the characteristics of the moving average which describes the trend of the averaged value.
- 2nd feature: F2 = (Close – MA10) – (Prev Close – Prev MA10).
  The purpose of selecting this feature is to observe whether the distance between the price and the MA10 is getting further up or further down.

- 3rd feature: F3 = RSI – MA10(RSI).
  The purpose of selecting this feature is to calculate the distance between the RSI line and the MA10 (RSI) line. When the calculation result of the 3rd feature is positive, it indicates that there is a tendency for the price to rise, and vice versa.
- 4th feature: F4 = (MA20 – MA50) – (Prev MA20 – Prev MA50)
  The purpose of selecting this feature is to see if the MA20 line is departing above the MA50 line, approaching or falling below the MA50. This feature is used to see the trend tendency of the price.
- 5th feature: F5 = Price Oscilator (PPO) value
- 6th feature: F6 = Momentum value
- 7th feature: F7 = Stochastic_K – Stochastic_D
  The purpose of selecting this feature is to see whether the Stochastic %K value is above the Stochastic %D or not.

Data Standardization and Splitting

The cleaned data is then standardized using the z-score function. This is carried out so that the data and features created have standardized values that do not differ considerably. The data is then divided into two parts, 80% data for training, and 20% data for testing, using the random_state=42 model.

Training data = 80%	Test data = 20%

Build the MLP Model

The Machine Learning model built in this research is Multilayer Perceptron using four hidden layers with each layer having 200, 100, 50, and 25 neurons. The activation function used is ReLU (Rectified Linear Unit) which is commonly used to overcome vanishing gradient problems. The optimization algorithm used is Stochastic Gradient Descent (SGD). The learning_rate is set to "adaptive" to adjust the learning speed according to the model performance, i.e. if the loss does not decrease, the learning speed will be reduced. The learning process is stopped using these criteria: change of the loss function is getting smaller below 1e-7 or the number of iterations is more than 1000.

Training and Testing the MLP Model

The next step is to train and test the model. The model has successfully trained for 9 selected stock data with an average loss of 0.00007099, and an average accuracy of 65.25%. Furthermore, the model is tested on testing data to obtain accuracy results on predictions and the confusion matrix.

RESULTS

The following are some snapshots of the results of running the system steps according to the research methodology. The "PWON.JK" stock data example obtained from Yahoo! Finance by eliminating the Adj Close column in pre-processing is shown in Figure 4.

```
            Open   High    Low  Close    Volume
Date
2014-01-02  270.0  280.0  270.0  280.0  44308000
2014-01-03  275.0  285.0  270.0  280.0  26494500
2014-01-06  280.0  282.0  269.0  269.0  31398700
2014-01-07  269.0  272.0  261.0  264.0  29343700
2014-01-08  265.0  276.0  265.0  275.0  32260400
...           ...    ...    ...    ...       ...
2023-12-21  432.0  434.0  428.0  430.0  14186700
2023-12-22  430.0  436.0  430.0  434.0  24600300
2023-12-27  434.0  448.0  430.0  446.0  53929200
2023-12-28  454.0  454.0  444.0  452.0  49469100
2023-12-29  452.0  454.0  446.0  454.0  24868100

[2481 rows x 5 columns]
```

Figure 4.
PWON Data Historical

After the data is retrieved from Yahoo! Finance, it is then automatically labeled by the system using the risk-reward ratio rule. An example of the result of automatic labeling into three classes for the stock "ASII.JK" is given in Figure 5.

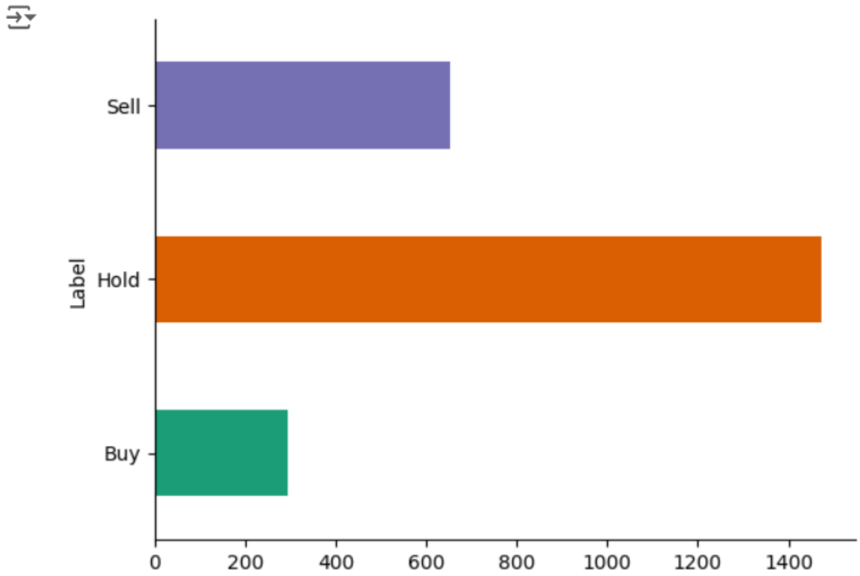

Figure 5.
Class Labeling

The results of adding MA5, MA10, MA20, and MA50 Moving Average values to the historical data of "PWON.JK" shares are given in Figure 6.

Date	Open	High	Low	Close	Volume	MA5	MA10	MA20	MA50
2014-01-02	270.0	280.0	270.0	280.0	44308000	NaN	NaN	NaN	NaN
2014-01-03	275.0	285.0	270.0	280.0	26494500	NaN	NaN	NaN	NaN
2014-01-06	280.0	282.0	269.0	269.0	31398700	NaN	NaN	NaN	NaN
2014-01-07	269.0	272.0	261.0	264.0	29343700	NaN	NaN	NaN	NaN
2014-01-08	265.0	276.0	265.0	275.0	32260400	273.6	NaN	NaN	NaN
...	...	...	...	...	...	...	...	...	...
2023-12-21	432.0	434.0	428.0	430.0	14186700	427.2	416.6	419.1	416.00
2023-12-22	430.0	436.0	430.0	434.0	24600300	429.6	419.4	419.5	416.20
2023-12-27	434.0	448.0	430.0	446.0	53929200	433.2	424.2	420.3	416.72
2023-12-28	454.0	454.0	444.0	452.0	49469100	438.8	429.2	421.5	417.40
2023-12-29	452.0	454.0	446.0	454.0	24868100	443.2	434.2	423.1	418.08

[2481 rows x 9 columns]

Figure 6.
Moving Average Feature

The test results of the machine learning system using testing data provide an average accuracy value of 65.2463%, with the accuracy value of each stock is given in Figure 7. The highest accuracy value was obtained by testing on BBCA stocks, amounting to 74.8454%. The lowest accuracy value was obtained by testing on PWON shares, amounting to 56.7010%.

```
Accuracy of ASII.JK: 0.6
Accuracy of TLKM.JK: 0.6907216494845361
Accuracy of PWON.JK: 0.5670103092783505
Accuracy of BBRI.JK: 0.6907216494845361
Accuracy of BBCA.JK: 0.7484536082474227
Accuracy of BNGA.JK: 0.6371134020618556
Accuracy of UNVR.JK: 0.6742268041237114
Accuracy of GGRM.JK: 0.5958762886597938
Accuracy of HMSP.JK: 0.668041237113402
```

Figure 7. Accuracy results for model test using test data

An example of the confusion matrix for three sample stocks, which are: ASII.JK, TLKM.JK, and PWON.JK is shown in Figure 5: ASII.JK, TLKM.JK, and PWON.JK is shown in Figure 8. The complete table of confusion matrices for all stocks is given in Table 1.

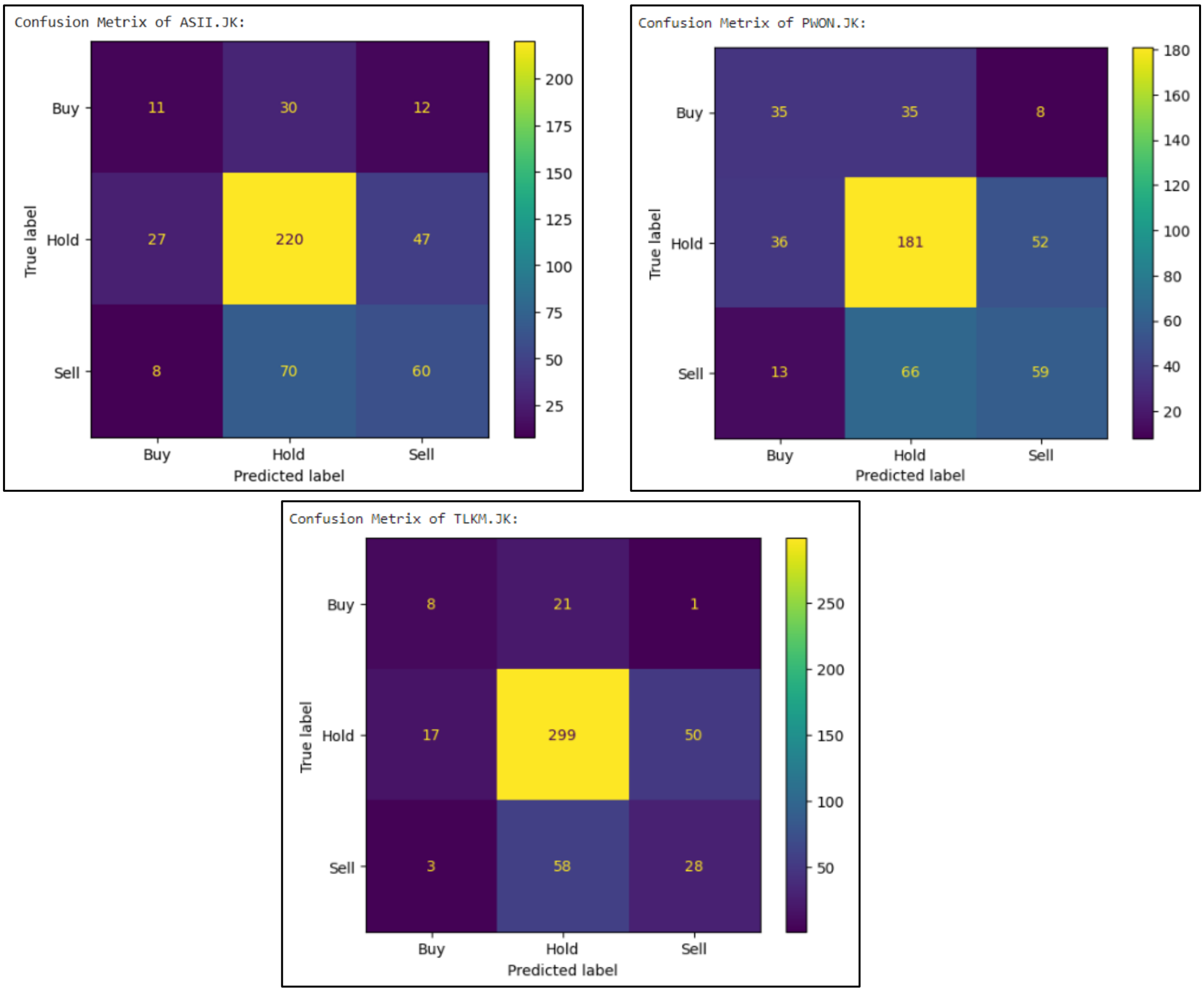

Figure 8. Example of Confusion Metrix

DISCUSSION, (font 12 Times New Roman)

Since the machine learning model is intended to support trading decisions, the confusion matrix is only labeled "Buy" and "Sell". The class labeled "Hold" should still be included in this classification model because, not every time a stock should be bought or sold, but sometimes we withhold from any action. The classes that require further action are the classes labeled "Buy" and "Sell", so the confusion matrix will be simplified to only two classes, namely "Buy" and "Sell". Profit calculation is done by calculating whether the action taken will provide profit or not by using the following formula.

Number of successes = (number of transactions that fulfill predicted buy and true buy) + (number of transactions that fulfill predicted sell and true sell)

Number of fails = ((number of transactions that fulfill predicted buy and true sell) + (number of transactions that fulfill predicted sell and true buy)

The formula is adjusted to the conditions in reality when we trade. When the prediction is "buy" and the result is also "buy" (in this case we will reach the profit target that we have set in the system, i.e. earn at least 6% profit after a 10-day lookup_period), then this is said to be a winning transaction. Likewise, when the prediction is "sell" and the result is also "sell" (in this case we will avoid experiencing a loss of more than 3% after a 10-day lookup_period), then this is said to be a successful transaction. Conversely, we are said to have a failed transaction, if we predict "buy", but after the transaction, it turns out to be a "sell", so we will suffer a loss. Similarly, it is also considered as a failure if we predict "sell", but it turns out to be "buy", so we lose potential profits. The confusion matrix that presents the prediction results with the actual results is given in Table 1.

Table 1. Confusion matrix for all stocks

			Predicted Label		Win-Loss (W/L) Ratio		
Stocks			**Buy**	**Sell**	**Buy Action**	**Sell Action**	**Average**
ASII	**True Label**	**Buy**	11	12	1.375	5	3.1875
		Sell	8	60			
TLKM		**Buy**	8	1	2.66667	28	15.33333
		Sell	3	28			
PWON		**Buy**	35	8	2.69231	7.375	5.033654
		Sell	13	59			
BBRI		**Buy**	33	4	3	9.5	6.25
		Sell	11	38			
BBCA		**Buy**	5	1	2.5	18	10.25
		Sell	2	18			
BNGA		**Buy**	33	10	4.125	5.9	5.0125
		Sell	8	59			
UNVR		**Buy**	8	7	1.14286	6.42857	3.785714
		Sell	7	45			
GGRM		**Buy**	23	15	4.6	3.93333	4.266667
		Sell	5	59			
HMSP		**Buy**	25	15	25	4.33333	14.66667
		Sell	1	65			
						W/L Average =	**7.531782**

Using the data from Table 1, the following discussions can be drawn:

- The overall average win-loss ratio of the 9 stocks is 7.5, or in other words there are 7.5 times more successful trades than unsuccessful ones.
- The largest win-loss ratio is 14.667 times on HMSP stocks, this is because in the table given, it is assumed that when we are asked to buy HMSP stocks (predicted "buy") for 26 transactions, among them there are 25 transactions which gives "true buy" results with a minimum profit of 6%, and only 1 transaction resulted in "true sell", which gives a loss of 3%. Likewise, when we are asked to sell HMSP stocks (predicted "sell") for 80 transactions, there are 65 transactions which provide "true sell", which protected us from a potential loss of 3%, and those that resulted "true buy" are only 15 transactions, which implies that we lost a potential profit of 6% in 15 times of profit opportunity.
- The smallest win-loss ratio is 3.1875 times on ASII stocks, this is because in the table given, it is assumed that when we are asked to buy ASII stocks (predicted "buy") for 19 transactions, among them there are 11 transactions which gives "true buy" results with a minimum profit of 6%, and 8 transaction resulted in "true sell", which gives a loss of 3%. Likewise, when we are asked to sell ASII stocks (predicted "sell") for 72 transactions, there are 60 transactions which provide "true sell", and those that resulted "true buy" are only 12 transactions.

"Based on the results obtained, the system built to predict 'Buy' and 'Sell' using a 1:2 risk-reward ratio can be considered successful, as it provides an average win-loss ratio of 7 times." The Risk-Reward Ratio of 1:2 was chosen as it represents a moderate risk-reward, providing measured and good risk management. The table provided is the result of the system using an input target profit of 6% and a target loss of 3%, which is commonly used by short-term traders. We will also conduct a study on different lookup periods in measuring target profit and target loss after this seminar. This study uses a 10-day lookup period in the context of short-term trading.

Furthermore, we also conducted a comparative study on the changes in target profit and target loss values applied to the system to observe the number of activityie and changes in the win-loss ratio. Of course, when the target profit and target loss amounts are increased or decreased, it will yield different results. In this study, total activity is calculated by summing the number of predicted buys that give true buy and true sell results with the number of predicted sells that give true buy and true sell results. Table 2 shows the observation results of the total activity and win-loss ratio for each profit target and loss target inputted to the system.

Table 2. Total activity for all stocks

No	Target Loss	Target Profit	Total Activity	Win-Loss Ratio
1	1,5%	3%	1734	2.782426
2	2%	4%	1309	3.67646
3	3%	6%	743	7.53178
4	4%	8%	462	7.61922
		Win-loss ratio average =		**5.40247**

Based on the results in Table 2, smaller target profit and target loss values result in a higher total number of 'buy' and 'sell' activities. This aligns with general trading practices. With smaller target profit and loss values, 'buy' and 'sell' activities occur more frequently. Conversely, if the target profit is increased, 'buy' activities become less frequent. With the same risk-reward ratio of 1:2, the win-loss ratio also positively correlates with the target profit and target loss values. In this case, a target profit of 3% and a target loss of 1.5% provides a win-loss ratio of 2.782 times, while a target profit of 8% and a target loss of 4% provides a win-loss ratio of 7.619 times.

CONCLUSION, LIMITATION, SUGGESTION

Conclusion

Based on the results of the research conducted, the machine learning system built can provide predictions for buying and selling activities well. The average win-loss ratio value of 7 times indicates that the predictions generated can provide a potential profit 5.40247 times compared to potential losses. The amount of target profit and target loss is positively correlated with the number of suggested transaction activities. Users can adjust the target profit and target loss values according to their risk type. Target profit and target loss parameter values are also positively correlated with the value of the win-loss ratio.

Limitation

The research was limited to only 6 stocks from the Indonesian stock exchange, namely: ASII, TLK, PWON, BBRI, BBCA, BNGA, UNVr, GGRM, and HMSP. The history data used is also only for 10 years. The number of layers used in the MLP algorithm is only 4.

Suggestion

Further research can be done by increasing the number of stocks used as samples. Research on the technical indicators used can also be carried out to obtain a better combination of technical indicators as input features. This research will also be continued by testing the reliability of the system using the Backtesting method using historical data for the period January 1, 2024 to November 30, 2024. By doing backtesting, it will be possible to evaluate the performance of the system before it is applied in real time trading.

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