Stock Market Trend Analysis and Machine Learning-based Predictive Evaluation

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Abstract

Financial experts may make successful selections thanks to the stock market's research and forecasting capabilities, which is exciting. This study examines the stock market forecast outcomes through a simple feed-forward neural network (FFNN) model. Then, we contrast those outcomes with those produced using more sophisticated Elman, fuzzy logic, and radial basis function networks. Any problem with finite input-output mapping may be solved using the FFNN as long as it has at least one hidden layer and a sufficient number of neurons. An ANN in which RBFs are used as activation functions is called a radial basis function network (RBFN). Utilizing the Levenberg-Marquardt Back Propagation technique, the FFNN and Elman networks are trained in this study. A Fuzzy Inference System (FIS) of Sugeno type is employed to replicate the predictive procedure within the realm of fuzzy logic. We choose the optimal RBF values using several clustering techniques. The approaches were validated using public stock market data on the National Stock Exchange of Indonesia.

Keywords: Stock Market Prediction, Elman Network, Fuzzy Logic, Neural Network Models, Radial Basis Function, Feed-forward Neural Network, Radial Basis Function Network.

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1 Introduction

The stock market is the place to do it for people looking to purchase or sell stocks or other securities. It is a security if anything has monetary value and can be bought, sold, or otherwise transacted. Investing in stocks may be done in either the main or secondary markets. An IPO is the first time a firm sells its shares to the general public on a major stock exchange. The procedure is identical to "going public" on the stock market. After the security has been sold in the main market, it will enter the secondary market, where one investor will buy shares from another at an agreed-upon price (Mathanprasad & Gunasekaran, 2022). The stock market consists of stock indexes, individual stocks, market regulators, investors, traders, and financial professionals. A "stock index" is a group of traded stocks. Financial stability is ensured by establishing market regulators by governments and other entities. The Indonesian Capital Market Supervisory Agency (Bapepam), the Bank Indonesia (BI), and the Indonesian Financial Service Authority (OJK) are the three main governing bodies for Indonesia's financial markets (Makarim and Taira, 2023). Speculative gains are the main focus of day traders, whereas steady growth is the focus of long-term investors in the stock market. A stock market expert ensures a level playing field for a particular asset (Dinesh, et al., 2021). Some economists believe that stock market forecasting relies upon different factors, like microeconomic factors and macroeconomic factors. Macroeconomic factors are difficult to predict as compared to microeconomic factors. However, investors in the stock market directly or indirectly are affected by the fluctuation of macroeconomic factors. As a result, anticipating macroeconomic trends in the stock market is crucial for making more profits (Dinesh, et al., 2021; Shah et al., 2021). Predicting upcoming stock prices within the financial market is known as stock market forecasting. Predicting the future price of stock properly may potentially provide large profits: high-frequency trading (HFT) and the efficient-market hypothesis (EMH) control stock market volatility.

Stock market forecasters put their efforts into developing techniques that accurately anticipate stock prices using globally recognized trading strategies. When it comes to input requirements and overall complexity, a successful anticipation model achieves the highest levels of accuracy with the fewest number of moving parts. Both private investors and government-affiliated organizations rely on forecasting methods for risk management and market surveillance. They provide analysts with a frame of reference for examining monetary concerns such as estimating cash-related subsidiaries and selecting a portfolio (Dinesh, et al., 2021; Goswami & Yadav, 2021; Selvin et al., 2017; Sinha et al., 2021).

Intelligent Trading Systems (ITS) are automated technologies stock brokers use to help them make rapid investment choices based on accurate price forecasts. It is widely accepted that stock market prices are dynamic and capable of rapid changes (Fang et al., 2014). This is because share market prices were also predicated on a combination of known characteristics (Prior day's final price, Price-to-Earnings [P/E] Ratio etc.) along with other components, and the financial space is inherently unpredictable. A skilled trader's ability to predict and act ahead of price movements in the stock market allows them to capitalize on price swings by either purchasing shares before they rise in value or selling them before they fall in value. This shows a direct correlation between the reliability of the prediction model and the advantage of utilizing the algorithm. However, expertise gained over years of practice by a single trader is hard to replicate (Idrees et al., 2019).

The main advantage of prediction is it enables accessibility of vital information to many parties that can be used to make choices about the future. As it is impossible to foretell the future with absolute precision, each forecast necessarily includes an element of inaccuracy. To a greater extent than usual, the margin of error increases the farther into the future one attempts to predict.

Changes in society, the economy, and government may all affect existing variables, and new factors can emerge. These inaccuracies arise because of the imprecision of the foundational data and the method used to make projections for the future. Because of this, choosing the right form of anticipation is crucial when looking into the future. Prediction, in general, makes use of numerical data rather than qualitative information like expert opinion. Nonetheless, quantitative data-driven forecasts provide more reliable results than their subjective counterparts.

Fundamental Analysis-Oriented Predictions

Predicting stock prices using Fundamental Analysis is a strategy stock market analysts use to forecast future price changes. To determine if the current market price for a firm is reasonable is identical to doing an analysis of the company's intrinsic worth. According to this school of thought, an investor may choose stocks that will beat the market and dependably profit from their investment by carefully analyzing each potential investment's market, economy, technique, management, product, and financial status. Examining how markets, industries, and enterprises are motivated by underlying constraints. It predicts future stock market behavior by analyzing economic, institutional, and firm-level data. It calls for a more comprehensive analysis of the market. The fundamental analysis rests on the concept that a flourishing economy encourages industrial advancement, which in turn encourages enhancements to existing organizations. The true value of a stock depends on the company's ability to acquire assets, which in turn is determined by the speculating environment and characteristics unique to the firm's external environment, competition level, management style, operating excellence, benefit, capital structure, and profit (Kimoto et al., 1990; Tan etal., 2005; Yoo et al., 2005). Fundamental analysts predict movements with the help of technical indication, which forms a candlestick pattern according to GDP, transactions, and other performance criteria for enterprises and commercial Value, as shown in Figure 1 below. The primary goal of this research was to provide aid to investors in identifying firms with potential for price appreciation throughout the holding period (so-called undervalued stocks):

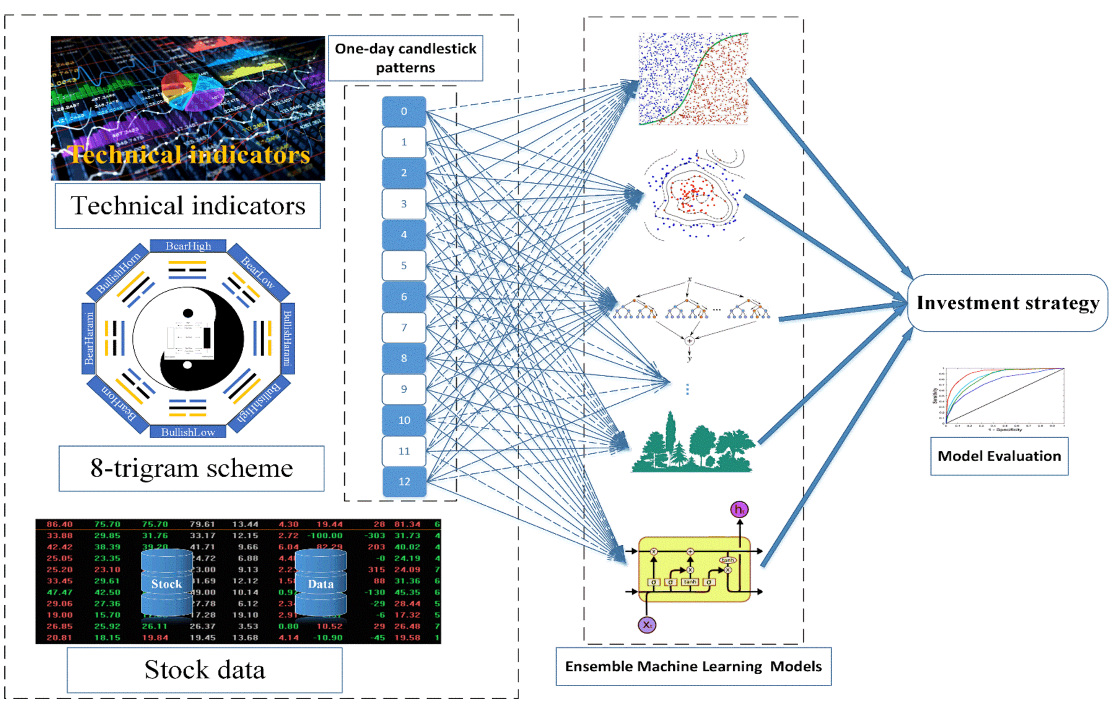

Figure 1: Overview of Prediction Framework

2 Literature Review

Mathanprasad & Gunasekaran (2022)'s objective was to obtain an accurate picture of the market's current situation via the examination of transactional data. According to them, the values of stock market data vary over time in response to changes in the perceived risk of the underlying assets. Thus, developing an automated computational procedure for predicting stock market data values is paramount. Data mining, with the help of stock market analysts and professionals, uncovers facts about variances in the stock market. The article's comparison research checked the accuracy of the suggested method's prediction by examining the efficacy of the new machine learning classification approach technique. Machine learning categorization systems currently allow for forecasting price and trend changes in the stock market. Let's analyze the algorithm's success and make ideas for future improvements based on these predictions. Users will easily identify which stocks will remain on the market for the longest. We increased forecast accuracy by analyzing the stock market using machine learning methods to 94.17%. By contrasting the outcomes, investors may be able to draw more accurate judgments regarding the firm's stock price.

The primary objective of this paper was to determine which machine-learning techniques are best at predicting stock prices (Makarim and Taira, 2023). Twelve articles were reviewed that discussed the application of machine learning and deep learning techniques to predict stock prices. In contrast to previous research, this one primarily considered the banking and healthcare sectors. Most top-performing articles across all fields have been shown to use either an extended short-term memory or a gated recurrent unit strategy. The study was limited mainly by its narrow scope and small sample size.

According to Dinesh, et al. (2021), traders may use the moving average, a technical analytical method, to better understand the direction of price movement and pinpoint profitable entry and exit locations in stock trading. The moving average is both an early and late predictor of a trend. In finance, a lagging indicator is a signal that is sent after a notable price shift has already taken place. This work focuses on A technical indication, which intends to use Machine Learning methods. To address this shortcoming, the suggested model used regression on shifting average values to speed up the delivery of the trade signal. Using the moving averages' trading signal, the model can foretell when the trend will reverse.

Twitter and other social networking sites have become prominent in recent years as vital forums for people to air their opinions ((Dinesh, et al., 2021). A firm's stock price may rise or fall as the number of people interacting with it increases and their opinion about the company changes. The article utilized machine learning and sentiment analysis to read the correlation between stock prices and Twitter trends and then forecasted the company's future stock price.

People's familiarity with the stock market is universal (Goswami & Yadav, 2021). Forecasting the direction of a stock's price is very difficult. If they can anticipate the market's direction, investors and traders will be better able to join and leave the market at optimal times. New deep learning-based systems were good at this, even if there are several approaches to predicting future prices. This study investigated the effects of epochs and batch size on a Long Short-Term Memory (LSTM) model used for in forecasting stock prices.

Predictive Analytics through Artificial Intelligence

One of the most adopted methods by most firms for attracting earnings, maintaining clients, and beating competitors is future forecasting and prediction. The current perspective on dealing with predictive and transforming corporate practices while maintaining ethics often involves converging approaches from the developing science of Artificial Intelligence. Predictive analytics, the most in-demand branch of data science, involves looking into the future by using statistical tools including machine learning algorithms, to make educated guesses about what will happen. Several applications have used ideas from machine learning and deep learning to make predictions, and these ideas have significantly influenced the field of predictive analytics (Tan et al., 2005; Yoo, et al., 2005; Zhang et al., 2018). Artificial intelligence (AI) algorithms are meant to train and learn over time from the examined data, making it possible to capture, maintain track of, analyze, and derive insights from massive amounts of data that would otherwise be impossible using conventional techniques. Though it was originally used to analyze consumer behaviour to increase sales and innovate marketing strategies, artificial intelligence is now being applied to a wide range of industries and verticals to simplify the complexity in enormous data to generate insights on sales and marketing.

The stock market holds a paramount position among various financial markets since it is where many organizations start by issuing and selling shares to the public. As a result, businesses may flourish and develop, which boosts the economy in many ways (new employment, steady inflows and outflows of capital, etc.). Investors gain the most from the stock market because it offers a venue for making investments and possibly, receiving dividends from those investments. When putting money into a business, investors must be prepared to handle anything that may go wrong. A great deal of data needs to be reviewed before making an investment and reaching a judgment that will provide the highest possible return. It used to be a very time-consuming process. Still, modern tools have made it possible to quickly and easily evaluate vast amounts of data, resulting in useful insights that may guide strategic decisions. One of the ways information is processed and the most useful results are produced through stock market apps, as well as the analysis of numerous approaches employing the many subtleties of mining patterns, machine learning, and deep learning. Investors make forecasts in the stock market by studying various data to invest, choosing when to purchase and sell shares, and maximizing profit and minimizing loss (Khodabakhsh et al., 2018). The stock market-related statistics utilized for forecasting came directly from the Indian stock exchange, including opening and closing prices, trading volumes, and more. Two banking-related datasets were utilized; both were culled from the Kaggle data warehouse. Models from ML and DL may be used to make predictions on prices and the movement of these prices since they can be seen as a regression issue based on time series. Linear regression, layers, and vectors, serve as the foundational elements in constructing neural networks, the basic concept of ML and DL methods (Raicharoen et al., 2003). In the layers, the data transforms due to mathematical procedures. Predictions are created using a set of bias and weight vectors chosen randomly; they are then compared to the target result, and the vectors are tweaked to improve future forecasts. This ongoing procedure concludes when underfitting or overfitting is absent, and the error rate between the forecast and the right targets is low.

Multiple Linear Regression

Multiple linear regression is an improved version of the classic linear regression technique. The aim is to estimate a single variable's value using the known values of two or more other variables. The value of the dependent variable cannot be approximated without the independent variables (Tan et al., 2005). There might have been a mix of continuous and categorical input-independent variables. A "dependent variable" is the thing that the prediction is made about. The regression coefficient quantifies changes in the dependent variable per unit of change in the uncorrelated variable.

Data forecasting, output prediction, time series analysis, and the identification of correlations are only a few of the many applications of this statistical technique. It may help to determine which potential confounding variables really affect the dependent variable. Multiple regression models have practical applications in various fields, from meteorology to predicting students' performance on standardized tests like the College Entrance Test (CET). Multiple linear regression is a tried-and-true statistical method that may be used in the study of the stock market (Yoo, et al., 2005).

Polynomial Regression

For users to fit a non-linear model to their data, the polynomial regression allows for the connection between the dependent variable y and the independent variable x is modeled as an n-th degree polynomial in x. Each original predictor is raised to a power, resulting in additional predictors. More and higher-order words are included as n becomes larger. Applying polynomials of higher order (square, cubic, quadratic, etc.) to one or more predictor variables achieves this goal (Zhang et al., 2018).

The model requires just one predictor and one outcome variable. Well-defined relationships between independent and dependent variables are one of its well-known benefits. Medical research, isotopes in the sediment, etc., are all possible applications. Here, a non-linear dataset is employed for training. The development of a stock market is never linear. Hence, polynomial regression may be used to anticipate future market behavior.

Decision Tree Regressor

For supervised learning, the Decision Tree is a popular practical technique. It is useful for Classification and Regression problems alike. It is possible to make predictions about both continuous and categorical outcomes (Fang et al., 2014). When dealing with issues involving making a choice, this algorithm is invaluable. Uses involve analyzing market expansion possibilities, using demographic information to locate prospective customers, etc. A tree-like model is trained using an object's characteristics to provide meaningful, stream-like results (Raicharoen et al., 2003).

The mean squared error is the primary metric to determine whether a node should be divided into two or more parts. Accuracy is determined by where and how strategic splits are made. In a decision tree, the root node is the highest-level node. A decision node occurs when a parent node splits into two or more descendant nodes. The elimination of sub-nodes from a decision node is referred to as pruning (Khodabakhsh et al., 2018). The leaf nodes are the terminal nodes at the tree's base. Typically, the root node will be at the top of the plot, and the leaf nodes will be at the bottom since this may be used with continuous dependent variables.

Random Forest Regressor

The random forest method works well with supervised learning. This technique is an ensemble learning approach to solving classification and regression issues. When numerous ML algorithms' predictions are pooled together, the resulting model outperforms the sum of its parts. Cross-validation is a technique that may improve accuracy. Given that random forests prevent overfitting, the maximum number of trees that may be run is unlimited.

A huge, higher-dimensional data collection may be worked on precisely by users. Forecasting diabetes, recommending products, tracking bitcoin prices, anticipating loan defaults, etc., are possible uses. The accuracy is dramatically increased by averaging the results from multiple separate classification decision tree fits performed on independent subsamples of the dataset, as is done by the Meta estimator. The output predictions synthesize the results of a chain of regression decision trees. For an output forecast, take the average of all the individual projections made by the trees in the forest.

3 Material and Method

Data Set

The prediction models have been trained on data from the National Stock Exchange (NSE) of Indonesia's stock market. Stock data from BNI, Bank Mandiri, Bank BRI, and Indonesian Capital Market Supervisory Agency (Bapepam) were been employed in the efficacy testing of the suggested methods. One-half of each dataset is utilized for instruction, while the other half is put through its paces in a test environment. The split between the test and training sets is shown in Table 1. The inputs are the opening prices from the previous ten days, and the output is the opening price from the next day (the eleventh day).

Table 1: Training and Testing Data

Stock	Training Period		Testing Period	
BNI	3/3/2022	2/9/2022	3/1/2023	3/3/2023
Bank Mandiri	3/9/2022	2/9/2022	3/1/2023	3/3/2023
Bapepam	3/9/2022	2/9/2022	3/1/2023	7/3/2023
BRI	3/9/2022	2/9/2022	3/1/2023	6/3/2023

Data Pre-processing

The data was standardized due to the widespread values. The normalization process converts quantitative values (such as counts or weights) into qualitative descriptors of significance. Since normalized values remove the impacts of some gross influences of the data, constructing the moved and scaled statistical versions is called normalization. To normalize data, we first transfer its range onto a new scale. Normalization is a necessary pre-processing step that brings the data nearer to the needs of the algorithm, making the algorithms' jobs easier. Data items (when all their properties have the same 'units'), variables (Standardizing to zero mean and unit variance, or within the range of [0, 1]), additionally, the target variable can also be normalized, often through a logarithmic transformation.

Techniques Used

This study examines the stock market forecasts using a simple feed-forward neural network (FFNN) model. Then, we contrast those outcomes with those produced using more sophisticated Elman, fuzzy logic, and radial basis function networks (Kim, J., 2022). Any problem with finite input-output mapping may be solved using the FFNN as long as it has at least one hidden layer and a sufficient number of neurons. An ANN in which RBFs are used as activation functions is called a radial basis function network (RBFN). Utilizing the Levenberg-Marquardt Back Propagation technique, the FFNN and Elman networks are trained in this study. A Sugeno-type fuzzy inference system (FIS) is used to simulate the prediction process in fuzzy logic. We choose the optimal RBF values using several clustering techniques.

Root Mean Square Error (RMSE)

It is a metric often applied to machine learning and deep learning to gauge the average deviation or error between forecasted and real values. It is a regression evaluation metric that quantifies the difference between predicted and ground truth values. RMSE is preferred over Mean Absolute Error (MAE) in certain scenarios because it gives higher weights to larger errors. By squaring the disparities between predicted and actual values, RMSE levies heavier penalties on bigger errors than MAE. This characteristic makes RMSE more sensitive to outliers or extreme values in the data. It measures how well the model's predictions align with the actual values, with lower RMSE values indicating better model performance.

4 Results

In Table 2, the Performance of the Proposed Techniques for the Bank Negara Indonesia (BNI) Stock are compared.

Table 2: Prediction Techniques for BNI Data Compared

Prediction Technique	RMSE	MMRE	Accuracy
FFNN	0.0121	0.0226	99.70
RBFN with Kmeans Clustering	0.0278	0.0324	98.72
RBFN	0.0225	0.0320	98.79
RBFN with Subtractive Clustering	0.0189	0.0325	98.68
TSK Fuzzy	0.0145	0.0168	98.99
Elman Network	0.0126	0.0168	98.97

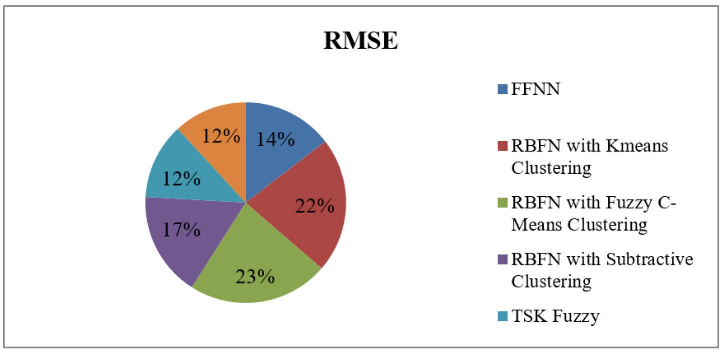

Figure 2: Graphical Analysis of Prediction Techniques for Bank Negara Indonesia (BNI) Data

Table 3: Prediction Techniques for Bank Mandiri Data

Prediction Technique	RMSE	MMRE	Accuracy
FFNN	0.0122	0.0218	98.92
RBFN with Kmeans Clustering	0.0222	0.0362	98.56
RBFN with Fuzzy C-Means Clustering	0.0306	0.0382	97.42
RBFN with Subtractive Clustering	0.025	0.027	98.82
TSK Fuzzy	0.0121	0.0210	98.77
Elman Network	0.0132	0.0260	98.55

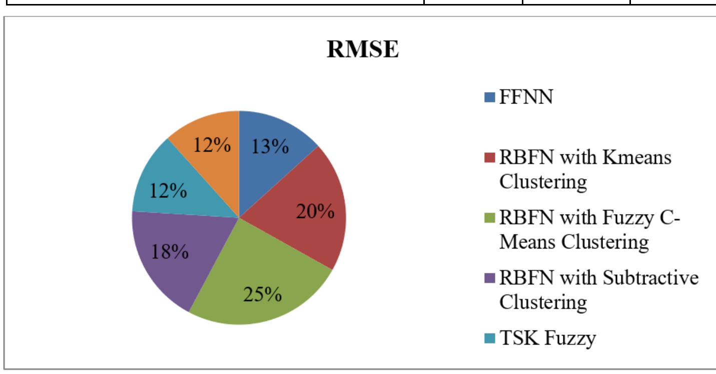

Figure 3: Graphical Analysis of Prediction Techniques for Bank Mandiri Data

Table 4: Prediction Techniques for Bank BRI Data

Prediction Technique	RMSE	MMRE	Accuracy
FFNN	0.0172	0.0361	98.72
RBFN with Kmeans Clustering	0.0421	0.0921	96.89
RBFN with Fuzzy C-Means Clustering	0.0401	0.0722	97.17
RBFN with Subtractive Clustering	0.0201	0.0389	98.28
TSK Fuzzy	0.0155	0.0201	98.62
Elman Network	0.0209	0.0402	98.33

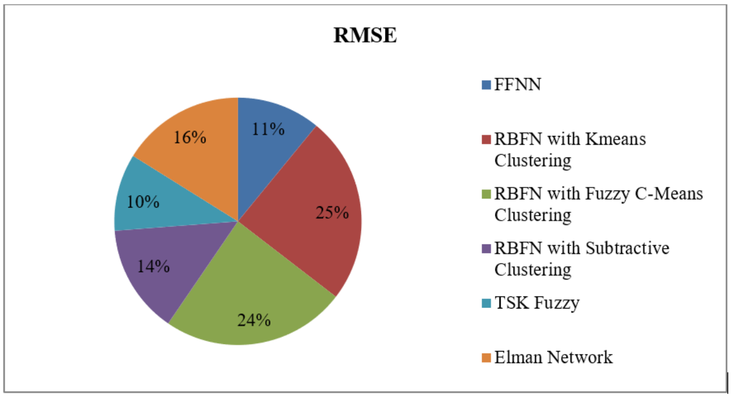

Figure 4: Graphical Analysis of Prediction Techniques for BRI Bank Data

Table 5: Comparison of Prediction Techniques for Data of Bapepam

Prediction Technique	RMSE	MMRE	Accuracy
FFNN	0.0182	0.0422	98.15
RBFN with K-means Clustering	0.0212	0.0945	98.07
RBFN with Fuzzy C-Means Clustering	0.0210	0.0801	98.23
RBFN with Subtractive Clustering	0.112	0.0402	98.77
TSK Fuzzy	0.0122	0.0362	98.69
Elman Network	0.0160	0.0252	99.12

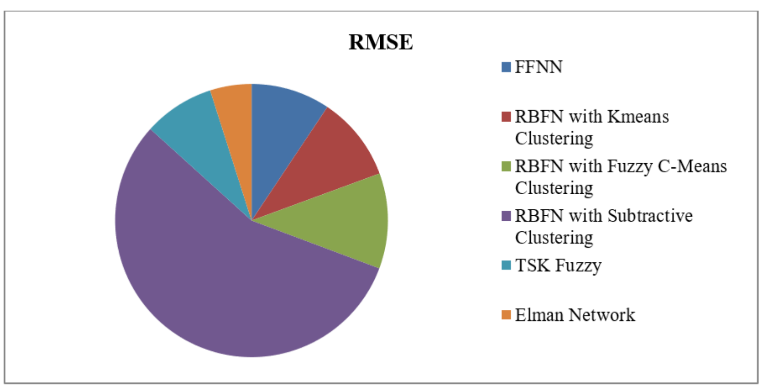

Figure 5: Graphical Analysis of Prediction Techniques for Bapepam Data

In the shifting average approach, the forecasted value is calculated as the average of the previous N values. In our case, we consider the current adjusted closing price as the mean of the adjusted closing prices from the preceding N days. The parameter N requires adjustment. Table 3, 4, 5, and Figure 3, 4, 5 display the RMSE between the actual and predicted values in the validation set for different N values. We select N=2 as it results in the smallest Root-mean-square deviation (RMSE).

5 Discussion

With the advent of machine learning techniques, researchers have been exploring their application in various fields, including stock market analysis and prediction, a crucial aspect of financial decision-making. Traditionally, this task was accomplished by using statistical models. But now machine learning techniques such as feed-forward neural networks (FFNN), radial basis function networks (RBFN), fuzzy logic, and Elman networks are being used to enhance the accuracy and efficiency of stock market trend analysis and prediction.

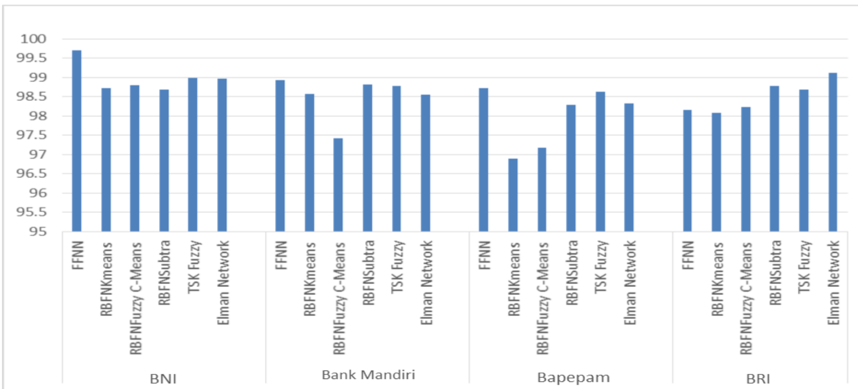

Figure 6: Prediction Accuracies of Different Machine Learning Applications

Feed-forward neural networks, known as multilayer perceptron, have been widely used for stock market trend analysis. They can be used to decode historical data on price shifts, like changes in stock values, and allow a search of any regularities (Yoo et al., 2005). FFNNs have shown promising results in predicting short-term stock market trends. Egeli et al. (2003) provided insight into the application of ANNs to predict the value of the Istanbul Stock Exchange index. The results suggested that ANNs outperformed traditional moving averages and showed promise in stock market prediction. This falls in line with the actual results obtained in various studies. Jabin (2014) used a feed-forward neural network to predict stock market trends and achieved 100% prediction accuracy. In the present study, the accuracy obtained using FFNN is 98.70%, 98.92%, 98.72% & 98.15% for BNI, Mandiri Bank, BRI & Bapepam, respectively (Figure 6).

Radial Basis Function Networks (RBFNs) are another machine learning technique used in stock market trend analysis. Unlike FFNNs, RBFNs have a different architecture with radial-based applications function to activate e hidden layers. RBFNs are known for their ability to approximate complex functions and adapt to various data types. They can capture patterns and relationships in stock market data and predict historical trends. RBFNs have demonstrated effectiveness in capturing long-term stock market trends. Rout et al. (2012) in their study on Exchange Rates concluded that the RBF-based forecasting model is the best choice for long-range forecasting of various exchange rates. Cheng et al. (2006) used the RBFN to develop a prediction model to forecast financial distress. They found that it was best in providing prediction accuracy compared to the Logit and backpropagation neural network models. The present study's predictive accuracies of RBFN K-mean clustering and RBFN Fuzzy C-mean clustering were very high and ranged from 96.89 % to 98.79 % (Figure 6).

Fuzzy logic provides a different stock market trend analysis approach by incorporating linguistic variables and fuzzy sets. It is defined by Guo et al. (2021) as "a qualitative approach for analyzing behaviors in complex systems, in which linguistic but not numerical variables are described". It allows for handling uncertainties and imprecise data common in financial markets. Fuzzy logic-based systems can create fuzzy rules based on expert knowledge or historical data. These rules can then be used to predict or evaluate stock market trends. Fuzzy logic techniques have successfully captured subtle market signals and dealt with the inherent vagueness in stock market data. Bernardo et al. (2013) presented a fuzzy logic system (FLS) for modeling and predicting financial applications using a new method that outperformed various machine learning models. Chang et al. 2008 presented a method using wavelet and Takagi-Sugeno-Kang (TSK)-fuzzy-rule-based systems. They achieved an accuracy of up to 99.1% by using simulation data projected the price fluctuation for stocks in the Taiwan Stock Exchange index. The average prediction accuracy was 98.8% using TSK Fuzzy logic for the present study (Figure 7)., and 99% was the highest for Bank BNI.

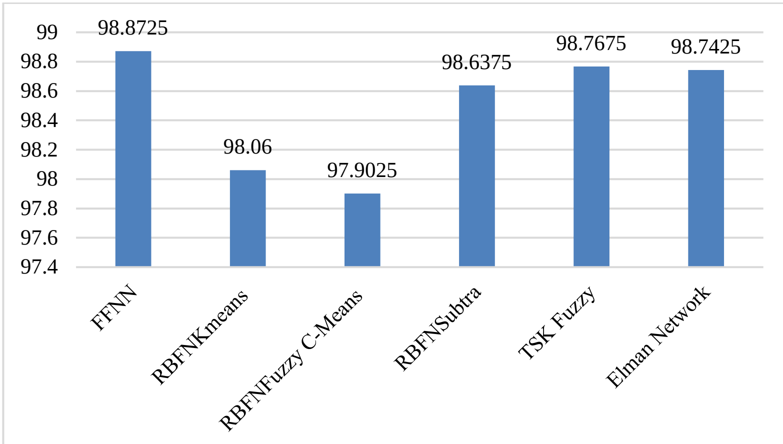

Figure 7: Average Prediction Accuracies

The average predictive accuracy in the present study, as observed in Figure 7 for Elman networks, is the second highest of all the techniques used, i.e., 98.7%. Elman networks, also known as recurrent neural networks (RNNs), are suitable for analyzing time series data, making them relevant for stock market trend analysis. Unlike FFNNs, Elman networks have feedback connections, enabling them to remember past information and capture temporal dependencies. This makes them particularly useful for capturing long-term trends and seasonality patterns in stock market data. Many researchers asserted that Elman networks show promise in forecasting stock market trends based on historical time series data (Krichene et l., 2017; Al-Akashi, 2022; Wu & Duan, 2017).

If we look across the different techniques used in the present study, considering the values obtained from Root-mean-square error (RMSE), the Mean magnitude of relative error (MMRE), and prediction accuracy, the TSK Fuzzy logic and Elman network were the best models for stock market prediction.

6 Conclusion

Machine learning techniques, such as FFNNs, RBFNs, fuzzy logic, and Elman networks, offer valuable stock market trend analysis and predictive evaluation tools. Each technique brings its strengths and advantages to the table. FFNNs excel in capturing short-term trends, while RBFNs effectively model long-term trends. Fuzzy logic can handle imprecise data, and Elman networks are suitable for time series analysis. The choice of technique depends on the specific requirements of the stock market analysis task and the nature of the data. Future research may explore hybrid approaches combining multiple techniques to enhance the accuracy and robustness of stock market trend analysis and prediction.

Neuronal networks have been used successfully for decades to predict time-series behavior based on previous data. This study compares and contrasts three different strategies for predicting the stock price of four firms using neural networks and machine learning. The results of a study comparing three different RBFN prediction methods—each employing a different clustering methodology to train RBF's parameters—show that the RBFN model using Layer-by-layer clustering achieves the lowest error and maximum accuracy. Comparing the three organizations' data to the standard FFNN model, the TSK fuzzy model, and the RBFN model with subtractive clustering, the Elman network model performed the best regarding error and accuracy (BNI, Bank Mandiri, BRI). TSK fuzzy only achieves its full potential on the JSP dataset regarding both error and accuracy. In this study, the open price is used throughout as an input and an output. Further research is needed to contrast those models to those other prediction models and use a wider range of factor indications as input to further improve the system's accuracy and efficiency.

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