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Research Article

Investigating the Impact of Data Volume on Stock Market Prediction: Insights from Artificial Neural Networks

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ABSTRACT

This study investigates the impact of varying data quantities on stock market prediction using Artificial Neural Networks (ANNs). It assesses short-term and long-term forecasts, considering time delays. ANNs, inspired by the human brain, are adept at recognizing patterns in intricate systems, making them suitable for stock market prediction. The research focuses on data from major IT and Telecom companies in the OMX30 Stockholm index. It utilizes specialized networks trained via supervised learning, conducting thorough testing to identify optimal setups. Results suggest that for short-term forecasts, reduced time delays lead to improved accuracy, and optimal configurations remain consistent with increasing data volume. However, conclusive insights for long-term predictions are not provided.

Keywords: Backpropagation, ANOVA, Configurations, Stock Prediction, Artificial Neural Networks.

INTRODUCTION

Predicting stock market trends involves navigating a complex landscape shaped by myriad factors. Conventional techniques often prove inadequate, prompting a shift towards more sophisticated technical and statistical modelling methods. Within this realm, Artificial Neural Networks (ANNs) have emerged as a promising avenue, owing to their capacity to capture nonlinear relationships in data [1]. This study harnesses the capabilities of ANNs to analyse stock market data, with a specific focus on Nordic large-cap stocks. Through Bayesian regularization backpropagation and rigorous statistical analysis, our aim is to deepen insights into market dynamics and enhance predictive precision [2]. Given the stock market's pivotal role as an economic barometer, accurate forecasting is imperative for informed decision-making in financial realms [3]. However, prevailing methodologies frequently lack robust frameworks for market estimation, resulting in subpar predictions. This paper posits that by refining cost predictions through machine learning (ML) algorithms, we can enhance accuracy in stock market forecasting [4].

Our research tackles the challenges inherent in stock market prediction methodologies by proposing an innovative approach that integrates multi-variable cost function optimization within a machine learning framework. This encompasses a comprehensive survey of existing ML-based stock cost prediction techniques, the formulation of an optimization-driven mathematical model, and empirical validation of the proposed methodology. This endeavour is motivated by the growing adoption of ML methodologies for predictive tasks and the recognition of their potential to elevate forecasting efficacy. Through optimized cost predictions, our research endeavors to advance the accuracy of stock market forecasting, thereby facilitating more informed decision-making in financial domains. Moreover, it aims to confront prevailing challenges and limitations in extant stock market prediction methodologies, laying the groundwork for more reliable and resilient forecasting techniques.

LITERATURE REVIEW

The paper [1] explores the use of Long Short-Term Memory Recurrent Neural Networks (LSTM-RNN) for predicting stock closing prices and trends. It highlights the limitations of traditional methods and demonstrates the effectiveness of LSTM-RNN through empirical analysis. The study contributes valuable insights into improving decision-making in financial markets.

In this study [5], the authors explore the application of machine learning techniques in fundamental analysis. They investigate how machine learning algorithms can be utilized to analyse fundamental financial data and make investment decisions. The research aims to assess the effectiveness of using machine learning in fundamental analysis and its potential impact on investment strategies.

This study [6] investigates the influence of oil prices and global market trends on the predictability of the Saudi stock market using a machine learning approach. By analysing historical data and employing machine learning algorithms, the researchers aim to assess the extent to which oil prices and global market indicators affect stock market movements in Saudi Arabia. The study aims to provide insights into the factors driving stock market predictability in the Saudi context and evaluate the efficacy of machine learning techniques in forecasting market trends under such conditions. This study [7] explores the use of learning-based methods for predicting stock trends by integrating technical indicators and sentiment analysis from social media data. By incorporating both traditional financial metrics and sentiment analysis of social media chatter, the researchers aim to enhance the accuracy of stock trend predictions. The study seeks to leverage machine learning algorithms to analyse historical data and social media sentiment, identifying patterns that could indicate future stock price movements. Ultimately, the research aims to develop a more comprehensive and effective approach to stock trend prediction by combining insights from financial analysis with sentiment analysis from social media platforms.

This research [8] investigates the relationship between competitive strategy and stock market liquidity using a natural language processing (NLP) approach. By analysing textual data related to competitive strategies employed by companies, the study aims to uncover how these strategies influence stock market liquidity. Utilizing NLP techniques, the researchers analyse textual data from various sources, such as company reports, news articles, and financial statements, to extract insights into competitive strategies. The findings aim to provide valuable insights into the dynamics between competitive strategy and stock market liquidity, offering potential implications for investors and policymakers. This study [9] investigates the behaviour of splice joints under various loading conditions, validating the findings through both experimental and numerical methods. Additionally, the study explores the potential of using artificial neural networks (ANNs) to predict the capacity of these splice joints. By conducting experiments and numerical simulations, the researchers aim to gain a comprehensive understanding of how splice joints respond to different types of loads. Furthermore, they seek to assess the accuracy and effectiveness of ANNs in predicting the capacity of splice joints based on input parameters. The study's results aim to contribute to the optimization and design of splice joints in structural engineering applications.

Forecasting Stock Market

Trends Predicting stock market movements is a complex task, involving the analysis of a multitude of factors that influence stock prices [5]. These prices are influenced by the interplay of supply and demand dynamics, which are in turn driven by variables such as company earnings and social media sentiment. Traders employ a combination of fundamental and technical analysis techniques to make accurate predictions. This paper focuses primarily on technical analysis, which involves analysing past price movements to forecast future trends in the stock market.

Within this domain, two key aspects warrant attention [7]:

Evaluation of Company Risks

Assessing the risks associated with individual companies is crucial for effective stock market prediction. Factors such as financial performance and industry trends play a significant role in determining the level of risk. Large-cap companies, characterized by their substantial market capitalization, are generally considered less risky than their small-cap counterparts [8]. This is because larger market capitalization provides greater stability. In contrast, small-cap stocks, with their lower market capitalization and higher susceptibility to immediate fluctuations and lower liquidity, are typically deemed riskier, making them less suitable for short-term investments.

Random Walk Hypothesis

The random walk hypothesis posits that stock prices follow a random path, challenging traditional prediction methods [10]. However, recent research has cast doubt on this hypothesis by revealing evidence of short-term predictability in stock prices [11].

Utilizing Technical Analysis

Technical analysis endeavors to forecast future price movements by scrutinizing historical market data, including price and volume, and employing chart patterns and statistical indicators [9]. This methodology operates on the premise that historical patterns tend to repeat themselves, diverging from the Efficient Market Hypothesis. Despite facing criticism, research findings substantiate its efficacy, leading many enterprises to rely on it for decision-making in markets such as Singapore [12-14].

Harnessing the Power of Neural Networks

Neural networks, drawing inspiration from the intricate workings of the human brain, comprise interconnected neurons organized into layers. These networks have the capability to discern intricate patterns from data and are commonly employed for predictive tasks. Artificial Neural Networks (ANNs) emulate the processing mechanisms of biological neurons, whereby input signals are processed to generate outputs. ANNs leverage extensive datasets for training, facilitating the learning of complex patterns and enhancing predictive accuracy.

Unveiling the Realm of Artificial Neural Networks

Artificial Neural Networks (ANNs), a subset of neural networks, find extensive application in tasks such as stock market prediction [15]. They are structured with input, hidden, and output layers, showcasing a robust architecture. Since their inception in 2008, ANNs have undergone significant evolution, spawning diverse models tailored to various domains. Their proficiency lies in discerning nonlinear connections, rendering them ideal for capturing the dynamic intricacies of the stock market. Employing abstract structures and backpropagation algorithms, ANNs continually adapt and learn, enhancing their predictive capabilities.

Delving into the Architecture of Artificial Neural Networks

The architecture of ANNs is characterized by interconnected neurons organized into layers. Each neuron processes input signals, applies a transformation function, and transmits the output to subsequent layers. Within ANNs, neurons and layers are interconnected via weighted connections, facilitating information flow. This paper adopts a three-layer architecture comprising the input, hidden, and output layers. Variations in network complexity stem from the configuration of single-layer and multi-layer architectures, dictated by the number of layers employed.

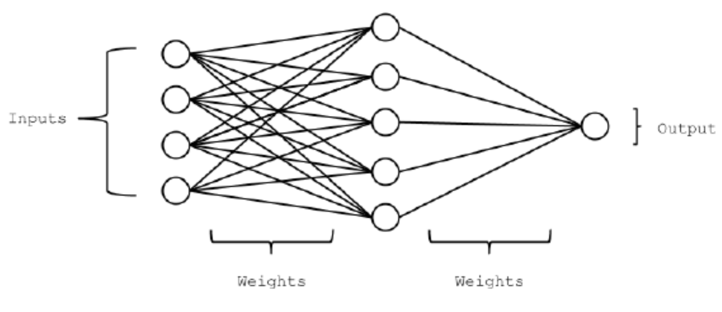

Figure 1 Simplified conceptualization of an ANN.

Figure 1 depicts a streamlined three-layer architecture of an Artificial Neural Network (ANN). At the outset, input data is received by the input layer, then undergoes processing within the hidden layer via weighted sums and activation functions. Ultimately, the processed information culminates in the generation of results by the output layer [16]. Notably, the hyperbolic tangent sigmoid transfer function, shown in Figure 2, serves as the activation mechanism in this study.

$$y = \tan sig(v) = \frac{2}{1 + e^{2m}} - 1$$

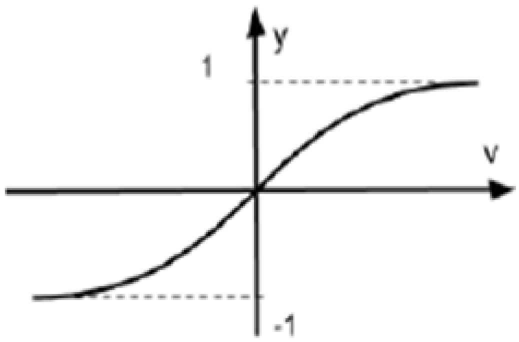

Figure 2 Tangent-shaped Sigmoid transfer function

Within the hidden layer, each neuron undergoes a process where it is multiplied by weights corresponding to connections with neurons in the output layer. These products are then summed to maintain numerical balance within the ANN. Mathematically, the structure of the ANN is represented by a matrix W, where w_{ij} signifies the weights between neurons in Layer A (input) and Layer B (hidden), with m neurons in Layer A and n neurons in Layer B. These layers are linked by vectors a_i and b_j, representing neuron outputs and inputs, respectively. Consequently, the flow of information within the network is captured by the equation $W_{a=b}$, wherein each weight wij in W is subject to adjustment during the learning process.

The learning process, facilitated by the backpropagation algorithm, entails fine-tuning input data along with associated weights. Historical data is typically partitioned into training, validation, and testing sets, although certain algorithms may utilize only training and testing data. For multilayer networks, the primary training technique involves the backpropagation algorithm, which iteratively adjusts weights to minimize errors and enable the network to learn from the training data. In this study, multilayer networks are augmented with the Bayesian Regularization backpropagation algorithm for enhanced training efficacy.

Unveiling the Backpropagation Algorithm

The backpropagation algorithm serves as a supervised learning technique employed for training Artificial Neural Networks (ANNs). It functions by propagating error gradients backward through the network, facilitating adjustments to connection weights. This iterative process aims to minimize disparities between predicted and actual outputs, enhancing the network's predictive accuracy [17].

Addressing Overfitting

Concerns Overfitting manifests in ANN models when they inadvertently capture noise present in the training data, resulting in suboptimal performance when applied to new, unseen data [18]. To mitigate this issue, regularization and cross-validation techniques are employed. Ideal stock market prediction models should adeptly capture patterns within the training data while also demonstrating robust performance on unseen datasets [19, 20]. Complex ANNs are particularly susceptible to overfitting, impacting the delicate balance between bias and variance. To enhance predictive accuracy, ample attention must be given to ensuring the availability of sufficiently large datasets for training purposes [20]

Harnessing ANNs for Stock Market Analysis

Artificial Neural Networks (ANNs) find extensive application in analysing and predicting stock market trends, leveraging historical data and a multitude of input features. The efficacy of ANNs in this domain hinges on various factors, including the quality of data and the architecture of the model. Recent studies indicate that ANNs surpass traditional statistical methods, particularly in short-term prediction scenarios, across diverse stock markets, including those in India and Nigeria [19, 21].

METHODS

This section delineates the methodologies employed in this study and sheds light on additional statistical techniques utilized.

Data Collection

The process of data collection for stock market prediction encompasses gathering historical stock prices, company financial data, market indices, and pertinent economic indicators. The quality and comprehensiveness of the dataset are pivotal for constructing robust prediction models. In this report, analysis is conducted on stock data pertaining to the Swedish IT and Telecommunication sector extracted from the OMXS30 index. The dataset spans four years for long-term analyses and two years for short-term perspectives, utilizing weekly means and daily data, respectively. Notable stocks included in the dataset comprise Axis, Ericsson B, Nokia Oyj, Tele2 B, and TeliaSonera, sourced from Nasdaq OMX Group, Inc.

Model Development

Model development, also known as implementation, encompasses the process of constructing and deploying prediction models utilizing machine learning algorithms. This process is illustrated in Figure 3.

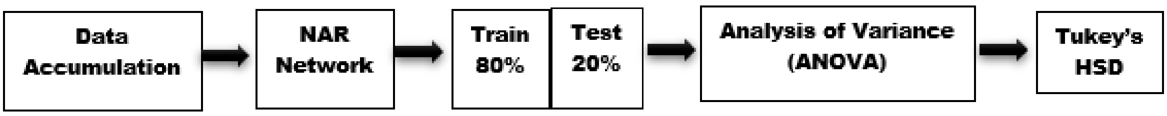

Figure 3 Schematic depicting the execution strategy for achieving both short and long-term goals.

The implementation of the Artificial Neural Network (ANN) using MATLAB [22] comprised constructing, training, testing, and evaluating the model. A nonlinear autoregressive network (narnet) was trained utilizing Bayesian regularization backpropagation following the data accumulation phase. The dataset was partitioned into 80% for training and 20% for testing purposes. Subsequently, statistical analyses, including ANOVA and post hoc tests, were conducted to ascertain significance. To mitigate overfitting, a single hidden layer with a maximum of 2 nodes was chosen for both short and long-term perspectives, aligning with prior research findings [23].

The calculation for the total number of parameters in the neural network architecture is determined by the formula:

$$(Input\ Nodes(Time\ Delaeys) * Hidden\ Nodes) + (2 * Hidden\ Nodes) + output\ Nodes$$

For instance, with 10 input nodes, 2 hidden nodes, and 1 output node, the total parameter count is 25. This ratio of 25:500, in comparison to the available 500 data points, ensures a significant difference range to prevent overfitting of the neural network.

Configuration Identification

Identifying configurations entails selecting suitable parameters and settings for the machine learning models [24]. This encompasses determining the neural network architecture, optimization algorithms, and hyperparameters.

Utilization of Bayesian Regularization

Bayesian regularization serves as a mechanism to counteract overfitting in machine learning by penalizing model complexity. It achieves this by updating weights and biases through backpropagation, thereby enhancing predictive accuracy and generalization. The integration of weight regularization with mean squared error minimization contributes to its effectiveness [20].

Evaluation Metrics

Performance measures are pivotal for assessing the efficacy of prediction models. It is imperative to employ a diverse range of metrics to evaluate the ANN's performance, as advocated by Ambrose [22]. This approach aids in validating results, mitigating bias, and reducing reliance solely on indices for decision-making purposes.

Mean Squared Error (MSE)

Mean squared error (MSE) serves as a metric for quantifying the average squared disparity between predicted and actual values. It provides a numerical evaluation of prediction accuracy, where a lower MSE signifies superior performance. Prior to statistical analysis, MSE facilitates the quantification of errors. It is calculated by squaring the differences between the predicted output (denoted by $\overline{ZY_\iota}$) and the actual output (denoted by ZYi) across N observations, employing the formula:

$$MSE = 1/M \sum_{j=1}^{M} \left(\overline{ZY_J} - ZY_j\right)^2$$

Indeed, this calculation offers a comprehensive evaluation of the model's predictive accuracy by taking into account all observations present in the dataset. By calculating the squared differences between predicted and actual values across the entire dataset and averaging them, the mean squared error provides a holistic assessment of how well the model performs in capturing the underlying patterns and trends in the data. This aggregated measure enables researchers and practitioners to gauge the overall performance of the predictive model, aiding in the identification of areas for improvement and refinement.

Statistical Analysis

Statistical analysis plays a vital role in evaluating the significance of the findings and making inferences about the predictive models. This encompasses:

Normality Assessment

Assessing normality entails testing whether prediction errors conform to a normal distribution, a crucial step for determining the appropriateness of parametric tests. Historical data from five enterprises underwent normalization using standard deviation and mean for subsequent analysis. The normalization process aimed to minimize differences in range for numerical stability and enhance convergence of the training algorithm. Unlike conventional approaches, normalization was initially applied solely to the training data in this report, with statistical metrics derived from it utilized for normalizing the testing data. Normalization was executed utilizing the mean (represented by μ) and standard deviation (represented by σ), calculated as:

$$ZP_u = \frac{ZP_u - ZP_{mean}(u)}{\sigma_q(u)}$$

Here, $ZP_{\text{mean}}(u)$ signifies the mean, and $\sigma_q(u)$ represents the standard deviation of the historical data, computed over a fixed length n_q containing 80 percent of the data. This normalization procedure was applied to both the training and testing data, yielding the disparity between the number of standard deviations of the data and its running mean.

Analysis of Variance (ANOVA)

ANOVA (Analysis of Variance) is employed to compare the means of multiple groups, determining whether statistically significant differences exist among them. In this study, ANOVA is applied under the assumption of a normal distribution within sample populations, which consist of historical stock data from various enterprises. The distinct configurations of each company serve as independent groups for analysis. Utilizing the one-way ANOVA function, the investigation aims to identify whether significant variations exist among the means of these groups, providing insights into which configurations yield the lowest errors.

Table 1 Analysis of Variance (ANOVA)

Source	SS	df	MS	F	Sig.
Between	SS_b	m-1	MS_b	Ms_b / Ms_w	p-value
Within	SS_w	n-m	MS_w		

Total	$SS_b + SS_w$	n-1			

Table 1 offers a comprehensive summary of the outcomes derived from the one-way test, elucidating the variability within the data via the sum of squares. It encompasses essential statistical parameters such as degrees of freedom, mean squared estimates, and significance p-values acquired from the F-distribution. The analysis centres on the means model, wherein observations are categorized according to group means and random errors. These outcomes are meticulously evaluated within the framework of the null hypothesis, shedding light on the presence of significant differences among the groups.

Underlying Assumptions

Before proceeding with one-way ANOVA testing, it is imperative to verify that three fundamental assumptions are satisfied to ensure the reliability of the results. These assumptions encompass normality, homogeneity of variances, and independence, all of which are indispensable for upholding the validity of statistical tests. Departures from these assumptions can exert a considerable influence on the accuracy of the test outcomes, as illustrated in Figure 3.

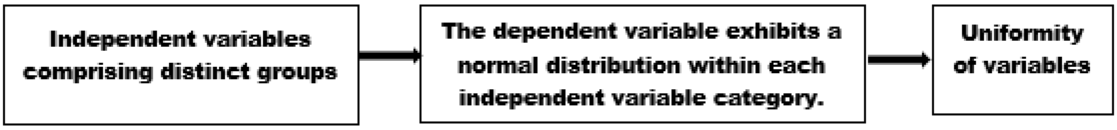

Figure 3 showcases the criteria necessary to meet before undertaking a one-way ANOVA.

All prerequisites for conducting one-way ANOVA were satisfied: the independent variables corresponded to enterprises, the dependent variables exhibited an approximate normal distribution, and variances across populations demonstrated homogeneity, as shown in Tables 2 and 3.

Table 2 Best outcomes for short-term analysis based on daily data.

Period (years)	Data points	MSE	Configurations
2	600	0.0402, 0.0376	2:1, 3:1
1.5	450	0.0325, 0.0301	1:2, 2:2
1	300	0.0547, 0.0513	1:3, 2:3
0.5	150	0.0451, 0.0427	1:4, 2:4
0.25	75	0.0738, 0.0662	1:5, 2:5

Table 3 Best results for long-term forecasting using weekly mean data.

Period (years)	Data points	MSE	Configurations
4	250	0.4321, 0.4253	1:3, 2:4
3.5	225	0.4113, 0.4038	1:3, 2:4
3	200	0.3765, 0.3857	2:4, 2:26
2.5	175	0.3902, 0.3946	1:4, 2:4
2	150	0.7589, 0.7426	1:4; 2:4
1.5	125	0.8374, 0.8123	2:15; 2:26

Hypothesis Testing

The null hypothesis stands as a declaration asserting no significant disparity or correlation between variables. Statistical assessments are utilized to either refute or fail to refute the null hypothesis based on observed data. A significance assessment was undertaken to discern disparities among group means, with the null hypothesis (H_0) positing that all group means are equivalent, while the alternative hypothesis (H_1) suggests that at least one group mean differs. A predetermined significance level (α), commonly set at 0.05, was established. Should the p-value derived from ANOVA fall below α, H_0 is rejected, signifying substantial variations among groups. However, ANOVA alone does not pinpoint specific discrepant groups, necessitating post hoc testing for further exploration.

Post Hoc Analysis

Post hoc tests serve to delve deeper into the outcomes of ANOVA tests and ascertain which groups exhibit notable differences from one another. Prominent post hoc tests include Tukey's Honestly Significant Difference (HSD) and Bonferroni correction. Subsequent to refuting the null hypothesis via ANOVA, Tukey's HSD method was employed for post hoc analysis to identify significant disparities among group means. This approach ensures an experiment-wise error rate of α=0.05, akin to ANOVA. Tukey's HSD entails pairwise comparisons of group means, computing:

$$zq_p = \frac{ZY_A - ZY_B}{ZSE}$$

for each pair, where ZY_A and ZY_B denote the means under comparison, and ZSE represents the standard error derived from the testing data. These zq_p values are juxtaposed against a critical value, $zq_{critical}$, derived from the studentized range distribution. Should zq_s surpass $zq_{critical}$, it indicates a noteworthy difference between the two group means. Tukey's HSD is renowned for its robustness, furnishing dependable outcomes even amidst multiple comparisons.

RESULTS

The results section encapsulates the outcomes of the study derived from the implemented methodologies and analyses. This encompasses the assessment of prediction accuracy, comparison of diverse models, and evaluation of statistical significance. We examined assorted data quantities for both short and long-term perspectives utilizing Artificial Neural Networks (ANNs). ANOVA was harnessed to compute Mean Squared Error (MSE), succeeded by a multicompanies test aimed at discerning significant disparities between groups.

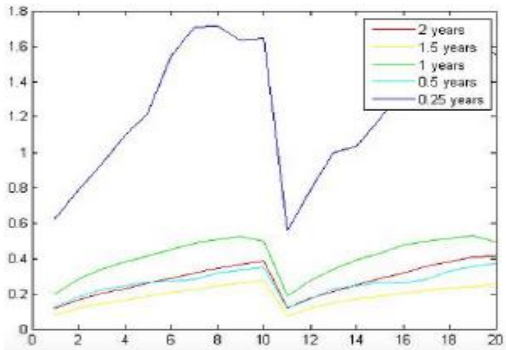

Figure 4.1 illustrates the multiple comparisons conducted among groups displaying significant differences.

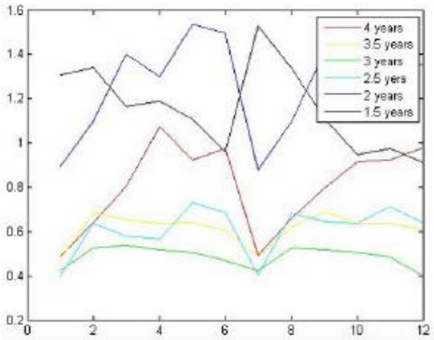

Figure 4.3 depicts the variances in optimal MSE discovered for the long-term perspective.

The graph illustrates trends in Mean Squared Error (MSE), with blue lines denoting minimal MSE, grey lines indicating insignificant variances, and red lines highlighting significant deviations. Short-term analysis retained optimal delay numbers, resulting in identical configurations with the lowest MSE. Both short and long-term perspectives favoured a single delay, yielding the lowest MSE with data from 1.5 years prior. Long-term predictions benefited from increased data volume, achieving the lowest MSE with two hidden neurons. Interestingly, optimal delay numbers varied widely, from 4 to 26 weeks, with a single hidden neuron, underscoring the significant impact of data quantity on prediction accuracy.

RESULTS ANALYSIS

The analysis of results assesses the efficacy of Artificial Neural Networks (ANNs) in stock prediction. Short-term analysis surpassed long-term, with minimal influence from escalating data quantity. Short-term predictions thrived on minimal delays, while long-term ones necessitated ample data and exhibited signs of overfitting. Short-term data consistently yielded the lowest error, affirming its aptness for ANN prediction. In summary, optimal configurations differed between short and long-term analyses, underscoring the pivotal role of data quantity and distribution.

LIMITATIONS

The limitations section delineates constraints potentially affecting the paper's outcomes, encompassing data quality, model assumptions, sample size, and result generalization. Key limitations include the inability to benchmark the ANN's efficacy against alternative methods, reliance on specific ANN specifications, and limited exploration of alternative AI approaches. Analysing enterprise data posed risks due to pronounced fluctuations, mitigated by focusing on relevant index sections and large-cap firms. Moreover, data distribution wielded notable influence, particularly in short-term analysis. Enhanced data handling could have bolstered research outcomes.

CONCLUSION

The conclusion succinctly summarizes the paper's key findings and implications for stock market forecasting. It underscores research objectives, discusses contributions to the field, and outlines avenues for future exploration. Notably, the paper elucidates significant discrepancies in optimal Mean Squared Error (MSE) between short and long-term perspectives using feedforward networks and statistical analysis models. While data quantity had negligible effect on optimal configurations for short-term analysis, it distinctly impacted long-term analysis. Additionally, the shortest time delay consistently yielded optimal results for short-term perspectives, whereas varying time delays across configurations for long-term perspectives preclude definitive conclusions. Future Research

The future research section outlines potential directions for further exploration, drawing on the findings and constraints of the present study. These avenues include exploring novel methodologies, addressing lingering inquiries, extending analyses to diverse datasets or temporal scopes, and exploring alternative strategies for stock market prediction. By delineating these avenues for future investigation, this section contributes to the ongoing advancement of knowledge in stock market prediction.

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