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Research Article

Enhancing Analytical Precision in Company Earnings Reports through Neurofuzzy System Development: A Comprehensive Investigation

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The object of research is the fundamental and technical indicators of companies after the release of the earnings report. This study attempts to address the issue of understanding the impact of fundamental and technical analysis indicator dynamics on profits and loss news releases. This research provides an in-depth analysis of stock price forecasting models, focusing on the influence of earning report seasons as catalysts for stock price growth. The study explores the relationship between key financial indicators, including earnings per share (EPS), revenue, and the maximum price observed in the 52-week period of the previous year (MaxW52). A trading algorithm is developed based on the adaptive neurofuzzy inference system (ANFIS). Through a comprehensive analysis of the neural network's training sample, it is concluded that abnormally large negative indicators have a profound impact on traders' emotional reactions. This results leads to a hypothesis for further research, suggesting that report indicators may be processed by computational algorithms, potentially including artificial intelligence (AI). Consequently, the emergence of emotional trading robots managed by investment funds becomes a crucial area for investigation. Understanding the behavior of these algorithms enables proactive decision-making, allowing traders to leverage their knowledge and sell-purchased securities to these algorithms before their transactions occur. The implications of this research shed light on the evolving landscape of trading strategies and the role of emotionality in financial markets.

1. Introduction

Making investment profits, diversifying assets, and receiving dividends are the main reasons why companies, banks, funds, investors, and traders buy and sell stocks [1]. The right purchase of stocks can help the investor's money grow. In the long term, the benefits of investing in stocks tend to far outweigh the benefits of storing money in less profitable assets such as cash or deposits [2]. The variety of stocks makes it possible to distribute risk during trading, as there is a large classification of assets, economic sectors, and geographic regions [3]. Investors can also receive income from the purchase of stocks in the form of regular dividends. They can keep this income or reinvest it.

The price of a stock is determined by the rule of supply and demand; until a reasonable price is reached, it will fluctuate between buyers and sellers. The ability to make a correct price forecast is the most important quality of a good trader [4]. As more people gain access to the stock markets due to the development of Internet technologies, more and more people are interested in finding out if there is any predictability in this market.

This study holds significant relevance in the field of finance, data analysis, natural language processing (NLP), and decision-making. The importance of gaining insight into the financial performance of companies cannot be overstated, making it essential to have an effective and efficient way to analyze earning reports. This research provides a solution to this critical need for investors, financial analysts, and decision-makers alike. Neurofuzzy systems coupled with NLP techniques offer an effective approach to glean valuable knowledge from the vast amounts of textual data in reports [5].

Analyzing business earning reports provides investors and financial experts the insight they need to make the right investment decisions, assess a company's debt-to-equity ratio, recognize any potential risks, and accurately predict future performance. Reading company earnings reports can be terribly time consuming as they often contain a lot of textual data. Extracting key elements and making correct conclusions can be quite difficult. The growing availability of vast amounts of financial data, coupled with advancements in artificial intelligence and machine learning, presents an unprecedented opportunity to revolutionize the way financial analysis is conducted. By combining the power of neurofuzzy systems with NLP, analysts and researchers can easily automate the analysis process and gain a better understanding of company financial performance. The integration of neurofuzzy systems with NLP enables the automatic extraction, categorization, and understanding of crucial information from unstructured earning reports, thus streamlining the analysis process. This advanced method offers an effective and reliable way to access in-depth insights [6]. Utilizing this method, financial analysis can be more precise and productive which can result in wiser decisions. Therefore, studies that are devoted to the development of a neurofuzzy system for analyzing company earnings reports using NLP are highly relevant in today's data-driven financial landscape.

NLP algorithms are essential in making sense of unstructured textual data and transforming it into useful, structured information. By making use of NLP algorithms including text parsing, named entity recognition, sentiment analysis, and topic modeling, this research has enabled extracting valuable information from financial statements and company earnings reports [7]. By implementation of certain techniques, it becomes easier to spot key financial indicators, patterns, and discrepancies that can give insights about the financial wellbeing and performance of organizations [8].

Neurofuzzy systems are a combination of artificial neural networks and fuzzy logic that works together to process complex and uncertain data [9]. This allows it to be more accurate than either technique alone. This research makes use of the capabilities of neurofuzzy systems to manage linguistic ambiguities and inexact financial data from earning statements. Neurofuzzy systems offer a convenient and clever way to develop algorithms with higher accuracy in predicting or classifying financial variables and making sense of complex linguistic expressions [10]. These sophisticated AI techniques make it possible to capture the intricate correlations between different data points.

The aim of the study is to create and evaluate a neurofuzzy system that can be utilized for interpreting corporate earnings reports with the application of natural language processing methods.

To achieve this aim, the following objectives are accomplished:

(i) It is necessary to design an architecture of an adaptive neurofuzzy system, which will take into account the process of collecting information from Internet resources, the process of processing indicators of fundamental and technical analysis, and the process of obtaining a neurofuzzy conclusion;

(ii) It is required to correlate the qualitative indicators of financial statements to filter the training data from unnecessary financial indicators;

(iii) To confirm the results of the study and build a financial strategy, it is necessary to conduct a predictive experiment; this experiment will help us to fix the fuzzy inference rules and optimize the trading strategy.

2. Literature Review

Traditionally, price analysis is divided into fundamental and technical analysis [11]. The stock price can be affected by news, events, and information about the release of new products. Information determines the movement of financial markets according to the efficient market hypothesis (EMH) [12]. The EMH model assumes that stock prices are determined by a random walk model. The EMH model does not allow us to predict the market movement. But a number of researchers have refuted this hypothesis. This study serves as a comprehensive evaluation of multiple classifiers in the context of predicting the direction of stock prices, aiming to provide insights into the performance and suitability of various machine learning techniques in this domain [13]. This article explores the relationship between Twitter mood and the Dow Jones Industrial Average (DJIA). The study analyzes Twitter feeds to determine if they are correlated with the value of the DJIA over time. The authors found that mood states, but not sentiment, can improve the accuracy of predictions of the DJIA. The article suggests that public mood state increases prediction accuracy and that emotions and moods play an important role in human decision-making [14]. This paper discusses the use of deep learning networks for stock market analysis and prediction. The study presents a comprehensive big data analytics process to predict the daily return direction of the SPDR S&P 500 ETF based on 60 financial and economic features. The authors explore various deep learning algorithms based on the combination of network structure, activation function, model parameters, and their performance depending on the format of the data representation. The article provides insights into the use of deep neural networks for stock market prediction and highlights the importance of data representation in achieving accurate predictions [15]. The authors of this research [16] propose a hybrid approach that combines the predictions of multiple classifiers to improve the accuracy of stock market predictions. The article provides insights into the use of machine learning techniques for stock market analysis and prediction and highlights the importance of combining multiple classifiers to achieve accurate predictions. It cannot be denied that macroeconomic indicators, seasonal effects, and political events can affect the price of stocks [17]. Emotions and moods also influence the decision to buy or sell stocks [18]. With the development of Internet technologies, the growth of information, and the improvement of methods of obtaining information, investors receive an ever-growing amount of information every day. Social networks have become a new platform for influencing investors' ideas and decisions. News sites broadcast thousands of news daily that instantly affect the stock market. Twitter, LinkedIn, and Facebook have made ordinary people become the main source of information exchange these days. Knowledge about finance, especially about the capital market, is spread instantly through social networks. The correlation between the behavior of the stock price, investor sentiment, and news is being investigated by many experts in the field of finance and natural language processing. The purpose of these studies is to find a new stock price forecasting tool.

Financial reports, official documents, and corporate online discussions can be used to predict market trends using fundamental analysis [19]. Reports, news, and articles about the company contain a lot of qualitative and quantitative information for fundamental analysis. The fundamental analysis is based on the company's financial conditions and macroeconomic indicators, such as EBITDA, P/E, profit, return on equity, and dividend yield. Using this information, traders trade stocks with a value above or below their intrinsic value.

As time series of financial indicators have become more accessible and easier to process, researchers in the field of stock price forecasting have shifted their focus to technical analysis [20]. The basis of technical analysis is chart patterns, relative strength index, moving averages (MAs), moving average convergence/divergence (MACD), and money flow index.

In recent years, text mining has been widely used in stock price forecasting. The text is converted into a feature vector [21]. There are many ways to vectorize text, namely, word embedding, the most common word embedding methods are BOW, N-gram TD-IDF, and Word2Vec; deep learning-based methods such as embedding layers in neural networks, using pretrained vectors such as Elmo and BERT; noun phrases; n-gram; topic modeling, which is similar to the clustering of numerical data and is used for classification of documents; emotional words; and the Bag-of-Words model is a disorderly representation of the document text.

This study proposes a knowledge-driven text-embedding model that is trained on over 10 years of annual reports from Russell 3000 firms [22]. The authors show that their proposed method outperforms cutting-edge benchmarks in predicting stock return volatility. This study provides insights into the use of BERT and natural language processing techniques for stock market prediction and highlights the importance of incorporating user sentiments in predicting stock market trends with [23]. This study proposes a deep learning framework that incorporates expert-based investment opinion signals to predict stock prices [24]. The authors of [25] proposed an ontology-based approach to extract word combinations for natural language processing. This research study proposes a method for financial forecasting using character n-gram analysis and readability scores of annual reports [26]. This study proposes a supervised topic model to extract focused topics and sentiment of financial markets for price movement prediction [27]. The study provides insights into the use of dimensional valence-arousal approaches for sentiment analysis in financial markets and highlights the importance of incorporating sentiment information in predicting stock price movements [28].

Behavioral economics explores how emotions significantly influence financial decisions [29]. The optimistic or pessimistic mood of the society is used in data mining or social network analysis. Sentiment assessment is used to understand what emotions people feel when they read news and opinions. Sentiment analysis is mainly applied at the following three levels: document level, sentence level, and aspect level. Sentiment analyzers are most often based on machine learning methods and lexicon approaches. In the lexical approach, the classifier determines the polarity using a dictionary, and the quality of classification depends on the size of the dictionary. Using natural language processing and text analysis methods, it is possible to determine the mood of text content, i.e., positive, negative, or neutral. Each term, word, or phrase that contains emotions is assigned positive and negative meanings. Furthermore, by the sum of these values, it is determined to which category the document belongs. The most commonly used dictionaries are WordNet, SentiWordNet, and SenticNet.

In complex analytical systems, machine learning algorithms are used after nlp-converting of text into numbers. By using SVM algorithms, a naive Bayesian classifier, and the random forest algorithm, the movement of stock prices can be forecasted. DNN, MLP, CNN, RNN, LSTM, and other types of neural networks are also used to predict stock prices based on time series analysis [30]. Moreover, regression models are used to evaluate the stock market. Regression is a random process used to describe specific time-varying processes in nature, economics, etc. The autoregressive model determines that the result depends linearly on its initial values and the stochastic term.

The description of stock returns can be represented by an extended ANFIS [31]. In general, fuzzy logic is effectively used in the building expert systems [32]. ANN and the fuzzy system, or ANFIS, were applied to predict the profitability of financial ratios of Islamic banks in Saudi Arabia [33]. ANFIS and discrete particle swarm optimization were applied to forecasting the closing prices of stock indices in India [34]. When developing such systems, it is important to use high-performance programming languages, for example, Python [35], as well as pay attention to the convenience of the user interface [36].

Data on prices of opening and closing trades or indicators of stock exchange indices are mainly used as a sample for training neural networks [31, 33, 34]. In our study, we tried to solve the problem of interpreting profit and loss news to further predict stock price movement. In our research, we will use EPS data, revenue, 52-week high price, price before the publication of the report, price at the opening of trading, maximum price during the trading day, closing price, analyst expectations, data from the previous financial report, and others. The main novelty of the study is the use of not only a time series of stock price dynamics but also the use of indicators of financial reports and indicators of experts' expectations in the projected predictive model. In the context of financial markets and stock price prediction using neural networks, most of the researchers [20, 30, 31, 33, 34] focused solely on time series data of price dynamics as the input to train their models. Considering the main aspects of this problem, we can say that using only time series about stock prices does not always lead to good results in research because relying only on the time series of price dynamics, which includes historical stock prices, might have limitations. Price dynamics alone may not capture all the relevant information about a stock's behavior. Financial markets are influenced by a multitude of factors, including economic indicators, news events, company fundamentals, and investor sentiment. Using only price dynamics might lead to overfitting, where a model becomes too specific to the training data and performs poorly on new, unseen data. Including additional features can help reduce overfitting by providing a more robust representation of the underlying factors influencing stock prices.

3. Materials and Methods

US companies publish their quarterly, semiannual, and annual financial results in certain calendar periods. Brokers call these time periods the reporting season. Quarterly reports are used to conduct fundamental and technical analysis of the company's financial position. Quarterly reports are used as an indicator of a company's development trends, and they are also used to predict the company's market price. The reporting season is one of the most important trading periods as volatility increases at this time. Volatility presents more opportunities for investors and traders to earn money through active speculation. Speculation manifests itself in an increase in the volume of traded stocks, as well as an increase in their range of price movements in general.

Earnings reports, also known as quarterly financial reports or earnings releases, are documents published by publicly traded companies to provide information about their financial performance during a specific period, usually on a quarterly basis. The Nasdaq stock exchange hosts a wide range of companies, and their earnings reports typically contain several key components. The following is an overview of the common elements found in these reports:

(1) Financial Statements. (1.1) Income Statement (Profit and Loss Statement). This section outlines the company's revenues, costs, and profits over a specific period. Key figures include revenue, gross profit, operating income, net income, and EPS. (1.2) Balance Sheet. This provides a snapshot of the company's financial position at a specific point in time. It includes assets (such as cash, inventory, and property), liabilities (such as debts and obligations), and shareholders' equity. (1.3) Cash Flow Statement. This document details how changes in the balance sheet and income statements affect cash and cash equivalents. It is divided into operating, investing, and financing activities.

(2) Management Discussion and Analysis (MD&A): This is a narrative section where company management provides context and analysis of the financial results. It often includes discussions on market conditions, business strategies, and significant events that impacted performance.

(3) Outlook and Forward-Looking Statements: Companies often provide guidance or outlook for future performance. This can include revenue projections, expected expenses, and other factors that may impact future earnings. In addition, companies include disclaimers about uncertainties and risks.

(4) Non-GAAP (Generally Accepted Accounting Principles) Financial Measures: In addition to standard accounting metrics, companies may present non-GAAP measures to provide additional insight into their performance. These might exclude certain expenses or income items to present a clearer picture of underlying business trends.

(5) Operational Metrics: Depending on the industry, companies may include key operational metrics relevant to their business. For technology companies, this might include user growth or engagement metrics, while a retail company might highlight same-store sales growth.

(6) Conference Call and Questions and Answers: Many companies conduct earnings conference calls where executives discuss the results, provide insights, and answer questions from analysts and investors. These calls offer an opportunity for stakeholders to gain a deeper understanding of the company's performance and future plans.

Speculation during the reporting season most often sets the price trend until the next report date, that is, for the whole quarter. Company executives prepare earning and loss statements. The correlation among the data on sales, income, losses of companies, as well as analysts' recommendations is most often studied in the reporting season. Companies hold teleconferences on financial and business results in the form of a discussion session, which is attended by analysts, investors, and journalists. A transcript of the recording sessions can be found on the companies' websites. At these meetings, company leaders present financial achievements and forecast future development plans. Detailed information is also provided on growth, risks, purchases, liabilities, lawsuits, stock repurchase programs, programs to increase or decrease the payment of dividends, in the management teams, and future goals of the company. The most important information is the EPS and revenue indicators, as well as their difference with analysts' expectations.

Publishing a large amount of data from the transcripts on the Internet may allow us to more accurately forecast the directions of stock price movements. In this regard, from all the catalysts listed in introduction, we have chosen the reporting season.

Our research begins with constructing a hypothesis about how earning reports affect investor sentiment and determine the ability to predict price movement based on data from earnings reports.

In this article, we conduct an extensive study of the possibility to predict the behavior of stock prices using data of EPS and revenue indicators, as well as their difference with analyst expectations, the price approximation to 52-week high until the report publication, price changes for the last quarter and for the same period of the report delivery, and price dynamics at the opening of trading after report publication. EPS is a fundamental metric that reflects a company's profitability on a per-share basis. It is widely used by investors and analysts to gauge a company's financial health. A company with growing or beating EPS expectations may be seen as financially sound and could experience positive stock price movements. Revenue is a critical measure of a company's top-line performance. Examining revenue indicators, such as total revenue and revenue growth, can provide insights into the company's sales and market position. Strong revenue growth is generally viewed positively by investors. Comparing actual results with analyst expectations provides an indication of how well the company performed relative to market forecasts. A significant difference between reported earnings and what analysts anticipated can lead to stock price movements as it may indicate surprises or deviations from market expectations. The distance of the stock price from its 52-week high can provide insights into the stock's momentum and potential resistance levels. Investors often look at this metric to assess whether a stock is trading near its peak or has room for further upside. Analyzing the stock price changes over the last quarter provides information on short-term performance trends. Investors may be interested in understanding how the stock has been moving in the recent past to identify potential patterns or trends. The immediate market reaction to earnings reports can be significant. Studying the price dynamics at the opening of trading after the report publication can provide insights into investor sentiment and reactions to the company's financial results. The data sample was taken randomly and was not tied to a specific time period. In order to reduce the volume of data and obtain more realistic figures of price dynamics, companies were selected by several indicators, primarily by the average trading volume of stocks per day, and this indicator amounts more than 100,000 stocks per day. Another filter for companies was the exclusion from the sample of several sectors of the US economy, such as fintechs, oil and gas industry, insurance, cryptocurrency. Some sectors, such as cryptocurrency, can be highly volatile and sensitive to external factors. Excluding these sectors might be a way to reduce the overall volatility of the sample and make the analysis more stable. Certain sectors, such as finance and cryptocurrency, are subject to specific regulatory environments that can significantly impact their performance. These regulatory changes may not affect other sectors in the same way. By excluding sectors with unique regulatory challenges, we can create a more predictable and comparable dataset. Oil and gas companies are heavily influenced by commodity prices, geopolitical events, and macroeconomic factors. Some sectors have unique financial metrics that are more relevant to their performance. For instance, financial ratios like net interest margin are critical for banks. Excluding sectors where traditional financial metrics may not be as applicable allows for a more targeted analysis using metrics that are relevant across the selected companies.

To solve the abovementioned hypotheses, a functional model will be designed using a neural network, which we will train on the collected data from financial reports. The main goal is to find a correlation between the dynamics of price changes and published report data. We transform the resulting model into a model of production rules. The rule base will serve as the basis for developing a fuzzy expert system for forecasting stock prices.

The financial indicators of the company that we used as a sample for the study are the following:

(i) EPS: earnings per share, or an indicator that determines the share of profit generated by the company, which accounts for one ordinary share outstanding [37]. EPS is calculated by dividing the company's net income by the average number of outstanding shares during a specific period. The formula for EPS is as follows: EPS = Net Income/Net In Average Number of Outstanding Sharescome

(ii) AnalyticEPS: EPS expected by analysts [38]. Analysts use their expertise, financial models, and industry knowledge to predict a company's future earnings and, consequently, its EPS. Analytic EPS is an important metric for investors as it provides insight into the market's expectations for a company's financial performance.

(iii) DynamicEPS: calculation formula for the difference of the current EPS with analysts' expectations, (EPS-AnalyticEPS)/AnalyticEPS∗100, indicated in %.

(iv) EPS_0: EPS for the last quarterly report [39].

(v) $AnalyticEPS_0$: EPS expected by analysts for the last quarterly report [38].

(vi) $DynamicEPS_0$: calculation formula for the difference of the EPS and analysts' expectations for the last quarterly report, $(EPS_0\text{-}AnalyticEPS_0)/AnalyticEPS_0*100$, indicated in %.

(vii) Revenue: revenue indicator [40]. Revenue is a key financial indicator that represents the total amount of money generated by a company from its primary business activities, such as sales of goods or services. Also referred to as sales or turnover, revenue is a crucial metric for assessing

a company's financial performance and overall health. The formula for calculating revenue is straightforward:
revenue = number of units sold * price per unit.
And, for service-based companies: revenue = number of services provided * price per service.

(viii) AnalyticRevenue: revenue indicator expected by analysts [41]. Analytic revenue, also known as analyst revenue, refers to the revenue estimate or forecast made by financial analysts who cover a specific company or industry. Similar to Analytic EPS, this metric represents the analysts' predictions about a company's future revenue based on their research and analysis.

(ix) DynamicRevenue: calculation formula for the difference between the current revenue indicator and analysts' expectations, (Revenue-AnalyticRevenue)/AnalyticRevenue*100, indicated in %.

(x) Revenue_0: revenue indicator for the last quarterly report [40].

(xi) AnalyticRevenue_0: analysts' expected revenue for the last quarterly report [41].

(xii) DynamicRevenue_0: calculation formula for the difference between the current revenue indicator and analysts' expectations for the last quarterly report, $(\text{Revenue}_0\text{-AnalyticRevenue}_0)/\text{AnalyticRevenue}_0*100$, indicated in %.

(xiii) MaxW52: the maximum stock price for the last 52 weeks [42]. This metric is commonly used in financial analysis and investment to provide insight into the historical performance of a stock. The maximum stock price over the past 52 weeks can offer information about a stock's recent trading range and potential trends.

(xiv) PriceBeforeOpen: stock price until the market opens after the report publication [42].

(xv) ClosenessW52: calculation formula for the difference of the stock price with the price of the one-year maximum used to understand the upper limits of resistance and also used to predict a possible gap in an uptrend, (MaxW52-PriceBeforeOpen)/PriceBeforeOpen*100, indicated in %.

(xvi) PriceOpen: stock price at the market opening, probable purchase price of the stock by the trading robot [43].

(xvii) DynamicPriceOpen: calculation formula for the stock price difference at the market opening with the price before the market opening after the report publication, (PriceOpen-PriceBeforeOpen)/PriceBeforeOpen*100, indicated in %.

(xviii) PriceDayTop: the maximum stock price on the day after the report is published; the first approximate selling price of the stock by the trading robot [44].

(xxi) DynamicPriceDayTop: calculation formula for the difference of the maximum stock price with the stock price at the market opening on the day after the report publication, (PriceDayTop-PriceOpen)/PriceOpen*100, indicated in %.

(xx) PriceClose: stock price at the close of trading on the day after the report publication; the second approximate selling price of the stock by the trading robot [45].

(xxi) DynamicPriceClose: calculation formula for the difference of the stock price at the close of trading with the stock price at the market opening on the day after the report publication, (PriceClose-PriceOpen)/PriceOpen*100, indicated in %.

(xxii) PriceOpen_0: stock price at the market opening for the last quarterly report [43].

(xxiii) PriceDayTop_0: the maximum stock price on the day after the report publication for the last quarterly report, necessary to verify the possibility of the origin of the gap [44].

(xxiv) $\text{DynamicPriceDayTop}_0$: calculation formula for the difference between the maximum stock price and the stock price at the market opening on the day after the publication of the last quarterly report, $(\text{PriceDayTop}_0\text{-PriceOpen}_0)/\text{PriceOpen}_0*100$, indicated in %.

(xxv) PriceClose_0: stock price at the close of trading on the day after the publication of the last quarterly report, necessary to verify the possibility of the origin of the gap [45].

(xxvi) $\text{DynamicPriceClose}_0$: calculation formula of the stock price difference at the close of trading with the stock price at the market opening on the day after the publication of the last quarterly report, $(\text{PriceClose}_0\text{-PriceOpen}_0)/\text{PriceOpen}_0*100$, indicated in %.

These indicators will be collected from the following sites using nlp scraping methods:

(i) https://finance.yahoo.com/quote/CDMO?p=CDMO&.tsrc=fin-srch

(ii) https://finance.yahoo.com/quote/CDMO/history?p=CDMO

(iii) https://finance.yahoo.com/quote/CDMO/profile?p=CDMO

(iv) https://www.investing.com/equities/peregrine-pharmaceuticals-earnings

(v) https://www.zacks.com/

The collected indicators will be transferred to an artificial neural network. The neural network will work on the Bayesian regularization algorithm. In the Bayesian structure, the neural network weights are treated as random variables, while the prior distribution of the network weights and the training sample are considered as a Gaussian distribution, so we have equation (1). A Sugeno-type fuzzy inference system will be modeled after training with data. The architecture of the adaptive neurofuzzy system is described in Figure 1.

$$\begin{aligned} P(D \mid \omega, \beta, M) &= \frac{e^{-\beta E_D}}{Z_D(\beta)}, \\ P(\omega \mid \alpha, M) &= \frac{e^{-\alpha E_\omega}}{Z_\omega(\alpha)}, \\ Z_D(\beta) &= \left(\frac{\pi}{\beta}\right)^{n/2}, \\ Z_\omega(\alpha) &= \left(\frac{\pi}{\alpha}\right)^{n/2}, \end{aligned} \tag{1}$$

where M is a specific neural network architecture. ω is the vector of network weights. N is the total number of network weights. $P(\omega \mid \alpha, M)$ represents a priori density. $P(D \mid \omega, \beta, M)$ is a likelihood function, which represents the probability of data occurrence, provided that the weights are given by ω. $Z_D(\beta)$ and $Z_\omega(\alpha)$ are the normalization coefficients. According to Bayes' rule, we get equation

$$P(\omega \mid D, \alpha, \beta, M) = \frac{P(D \mid \omega, \beta, M) P(\omega \mid \alpha, M)}{P(D \mid \alpha, \beta, M)}, \tag{2}$$

where $P(D \mid \alpha, \beta, M)$ is the normalization coefficient and has nothing to do with the weights of the network, which guarantees that the total probability will be equal to 1.

In order to read various data located on the above-mentioned web pages, web scraping methods are used to systematize and further analyze the collected indicators. In fact, the information is collected and exported into a more convenient tabular format. In this way, we will be able to automatically receive new or updated data for the successful collection of the training sample. When scraping, we will use the JavaScript libraries for Node.js that control the Chrome browser without a user interface. With the help of this library, it is quite easy to automatically read data from various websites or create so-called web scrapers that simulate user actions.

The developed scrapper collected data from 98 company reports for 2022. The difficulty in collecting data was to determine the exact time of the report release. Companies can announce the report before the market opens or after the market closes. This means that the information published in the report after the close of trading begins to affect the stock price only the next day. The structure of this data is described in Figure 2.

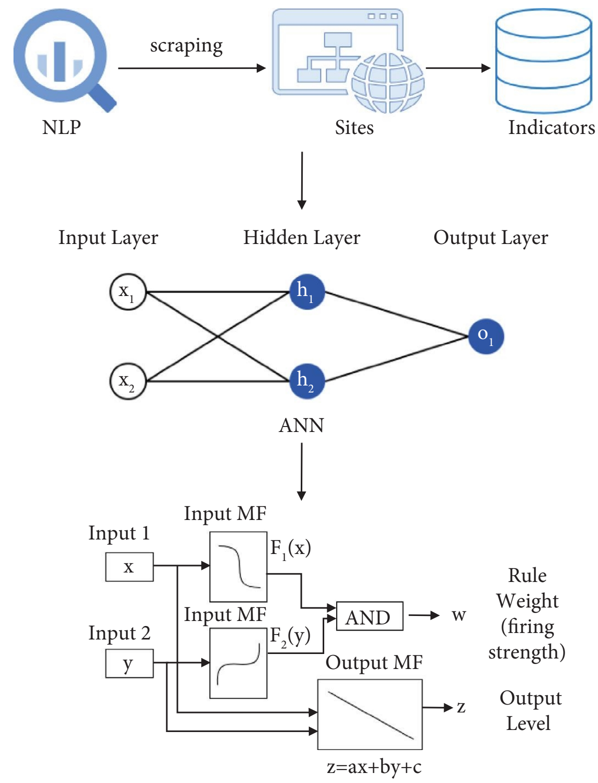

Figure 1: Architecture of an adaptive neurofuzzy system.

4. Results and Discussion

4.1. Correlation of Qualitative Indicators of Financial Statements. 2022 was a year of turmoil for the global economy. The complexity for the economy is caused by the following events: the bursting of the bubble of technology companies that have grown during the period of COVID-19; military conflict in Ukraine; tightening sanctions against Russia; rise in price of energy resources; and large rise in inflation. Conducting a study on price forecasting in an economically unstable period will make it possible to build a more flexible forecasting model that will be will be resistant to the formation of new economic crises. It should also be noted that we avoid the strategy of keeping stocks on hand for a long time. This research is conducted under the investment strategy "bought today, sold today". A change in the text in Figure 2 to green color means that the report's indicators exceeded the expectations of experts and red color means that the indicators did not reach the expectations of the market. The yellow colored columns indicate the percentage change of the previous columns. These qualitative indicators will be used in the analysis of the correlation to the price. The green columns are the purchase prices and the minimum selling price. Orange columns are qualitative indicators of probable profit on the trading day. All qualitative indicators were sorted and are shown in Table 1, and the correlation between them is displayed in Table 2. Correlation analysis consists of determining the degree of relationship between two random variables X and Y. The correlation coefficient is used as a measure of the closeness of such a relationship. The correlation coefficient is estimated from a sample size of n related pairs of observations (x, y) from the joint population of X and Y. A linear correlation coefficient in r is used to estimate the degree of relationship between the quantities X and Y measured in quantitative scales, assuming that samples X and Y are distributed according to the normal law.

Industry:	ticker	Market Cap	avg volume	MaxW52	date	EPS	Analytic EPS	DynamicEPS	EPS0	Analytic EPS0	DynamicEPS0	Revenue	Analytic Revenue	DynamicRevenue	Revenue0	AnalyticRevenue0	DynamicRevenue0	PriceBeforeOpen	ClosenessW52	PriceOpen	DynamicPriceOpen	PriceDayTop	Dynamic PriceDayTop	PriceClose	DynamicPriceClose	PriceOpen0	PriceDayTop0	DynamicPriceDayTop0	PriceClose0	DynamicPriceClose0
Grocery Stores	ACI	11.21B	5584840	37.99	Oct 18, 2022	0.72	0.651	10.58209184	1	0.96	4.6462955	17.92	17.71	1.18577	23.31	23	1.3478	26.43	43.738176	26.80	1.39992	26.86	0.2238806	26.74	-0.2239	26.65	26.98	1.2382739	26.52	-0.48780488
Software—Application	SOUN	253.331M	359696	18.14	Nov 1, 2022	-0.15	-0.15	0	0.36	0.19	89.473684	11.2	8.2	36.5854	6.15	6.22	-1.125	1.8900	859.78836	.3300	23.2804	2.6200	12.446352	.8100	-22.318	3.6000	3.7700	4.7222222	3.5700	-0.83333333
Airports & Air Services	UP	316.804M	1504678	4.7600	Nov 09, 2022	-0.36	-0.25	-44	0.3	0.25	18.04	420.4	381.4	10.211	425.51	366.91	15.971	1.6300	192.02454	6100	-1.227	1.6200	0.621118	.5000	-6.8323	2.6000	2.6700	2.6923077	2.5500	-1.92307692
Marine Shipping	MATX	2.409B	418293	125.34	Nov 02, 2022	6.89	7.07	-2.54596888	9.49	8.81	7.7185017	1.11	1.1	0.90909	1.26	1.27	-0.787	74.87	67.410178	73.87	-1.3356	75.07	1.6244754	71.11	-3.7363	91.99	92.10	0.1195782	91.26	-0.79356452
Trucking	MRTN	1.728B	370104	23.43	Oct 18, 2022	0.32	0.341	-6.18586925	0.39	0.321	21.268657	324.4	322.1	0.72646	329.57	290.7	13.371	20.00	17.15	20.19	0.95	20.56	1.8325904	18.52	-8.2714	17.56	20.49	16.685649	20.21	15.09111617
Software—Application	SAP	131.89B	1364332	141.69	Oct 25, 2022	1.12	1.22	-8.19672131	0.978	1.09	-10.238532	7.81	7.51	3.99467	7.66	7.58	1.0554	91.01	55.686188	96.58	6.12021	97.29	0.7351419	96.32	-0.2692	87.84	90.35	2.8574681	90.29	2.789162113
Airlines	UAL	14.44B	9226047	53.12	Oct 19, 2022	2.81	2.28	23.24561404	1.43	1.85	-22.702703	12.88	12.74	1.0989	12.11	12.12	-0.083	37.25	42.604027	39.32	5.55705	40.35	2.619532	39.10	-0.5595	38.82	38.97	0.3863988	37.44	-3.55486862
Telecom Services	AMX	64.135B	2121472	22.65	Oct 18, 2022	5.63	5.71	-1.40105079	4.36	8.27	-47.279323	214.4	216.0	-0.7221	217.39	216.09	0.6016	16.64	36.117788	16.74	0.60096	16.81	0.4181601	16.35	-2.3297	19.60	19.70	0.5102041	19.09	-2.60204082
Semiconductor Equipment & Materials	ASML	248.869B	1370696	817.30	Oct 19, 2022	4.2	3.75	12	3.62	3.6	0.5555556	5.66	5.49	3.09654	5.55	5.54	0.1805	398.99	104.84223	15.89	4.2357	431.85	3.8375532	424.02	1.95484	492.90	516.76	4.8407385	514.42	4.36599716
Aerospace & Defense	LMT	127.156B	1437634	494.66	Oct 18, 2022	6.87	6.66	3.153153153	1.16	1.88	-38.297872	16.58	16.66	-0.4802	15.45	15.98	-3.317	397.31	24.502278	03.15	1.46988	435.51	8.026789	431.84	7.11646	378.82	390.57	3.101737	390.38	3.051581226
Integrated Freight & Logistics	JBHT	19.039B	770086	218.18	Oct 18, 2022	2.57	2.45	4.897959184	2.42	2.35	2.9787234	3.84	3.8	1.05263	3.84	3.6	6.6667	165.75	31.631976	70.04	2.58824	171.14	0.6469066	167.89	-1.2644	168.85	175.04	3.6659757	174.46	3.32247557
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...

Figure 2: Fragment of the collected data of financial reports.

The correlation results show that the daily maximum income, when buying a stock at the opening price, strongly depends on EPS and revenue, i.e., the main indicators of the financial report. It has also been observed that the dynamic price indicator is positively correlated in a weaker form with the closing price and the distance from the yearly high price. It was also discovered that last year the opening price of trading and the closing price of trading were strongly correlated with each other. These indicators are explained by the fact that 2021 was a good year in economic terms for many companies; many companies were on the rise after the lifting of restrictive measures in connection with COVID-19. It also indicates the absence of strong volatility during one trading day in 2021. And in 2022, companies are increasingly experiencing both a sharp rise in price and a sharp drop in price during one trading day. It has also been discovered that to a small extent, the closing price is negatively correlated with the yearly high price. That is, it can be concluded that if a company has submitted a bad report but the current price of the company is far from the price of a yearly maximum, then the drop will be minimal, and vice versa, if a company has submitted a bad report and is close to the price of a yearly maximum, then the drop will be maximum. Also, if the company has submitted a good report but the current price of the company is far from the price of a yearly maximum, then the growth will be maximum, and vice versa, if the company has submitted a good report and is close to the price of a yearly maximum, then the growth will be minimal. It is impossible to take into account correlation calculations with price dynamics indicators for the past time since the indicator of a yearly maximum in the past was different.

4.2. Price Prediction Experiment for Building Trading Strategy. Based on the correlation results, we chose DynamicPrice as the output parameter and DynamicEPS, DynamicRevenue, and ClosenessW52 as the input parameters. We will not use DynamicPriceClose as an output parameter because it correlates worse with other variables than DynamicPrice. We will also bring these parameters to normalization in the range from −1 to +1. A fragment of normalization data is shown in Table 3.

Based on these data, we will train the neural network. 70% of the sample data will be used for training, 15% for validation, and 15% for testing. The neural network will consist of 50 layers and work on the Bayesian regularization algorithm. Traditional neural network models consider mean squared errors (MSEs) as a learning objective function and do not optimize the network weights.

The training results are described in Figure 3. Also, Figure 4 presents a series of graphs of training states, i.e., gradient, Mu, number of parameters, sum of squares of parameters, and validation check depending on epochs. Figure 5 shows the graph for obtaining the best training performance indicator = 0.000609 received at epoch 983. In Figure 6 is described the error histogram chart and indicators of training regression $R = 0.68741$, testing regression $R = 0.16651$, and general regression $R = 0.54211$.

After testing, the regression became equal to $R = 0.51539$. The test schedules are described in Figures 7 and 8.

The received error result of neural network is generally good and is equal to 0.000609. But to develop an algorithm for buying and selling securities, we will need an expert system. To solve this problem, we have modeled an adaptive neurofuzzy inference system. The training took place in 100 epochs, and the minimum RMSE was 0.0260256. Figure 9 shows that RMSE stopped changing after the 7th epoch. The model of ANFIS production fuzzy rules is presented in Figure 10. In Figure 11 are shown the surfaces of 3 input and 1 output variables.

Since we previously said that we avoid the strategy of holding stocks for a long time, our algorithm will be based on making a profit during one trading day. Although studies [11, 15, 19] indicate that good profits can be expected during the month, the indicators of a good financial report set the general trend in the dynamics of the company's stock price chart. However, we still want to maximize the annual income of the portfolio by increasing trading operations with a small amount of invested money. This study is conducted under the investment strategy "bought today, sold today". An analysis of the indicators of the goals and the ANFIS model is described in Table 4. When expecting income above 5%, data in excess of 5% of the output variable of the ANFIS model can be used.

Table 1: A fragment of qualitative indicators of financial reports.

Dynamic price DayTop	Dynamic EPS	Dynamic EPS_0	Dynamic revenue	Dynamic $revenue_0$	Closeness W52	Dynamic PriceOpen	Dynamic PriceClose	DynamicPrice $DayTop_0$	Dynamic $PriceClose_0$
0.223881	10.58209	4.646296	1.185771	1.347826	43.73818	1.399924	−0.22388	1.238274	−0.4878
12.44635	0	89.47368	36.58537	−1.1254	859.7884	23.28042	−22.3176	4.722222	−0.83333
0.621118	−44	18.04	10.21104	15.97122	192.0245	−1.22699	−6.8323	2.692308	−1.92308
1.624475	−2.54597	7.718502	0.909091	−0.7874	67.41018	−1.33565	−3.73629	0.119578	−0.79356
1.83259	−6.18587	21.26866	0.72646	13.37117	17.15	0.95	−8.27142	16.68565	15.09112
0.735142	−8.19672	−10.2385	3.994674	1.055409	55.68619	6.120207	−0.26921	2.857468	2.789162
2.619532	23.24561	−22.7027	1.098901	−0.08251	42.60403	5.557047	−0.55951	0.386399	−3.55487
0.41816	−1.40105	−47.2793	−0.72212	0.601601	36.11779	0.600962	−2.32975	0.510204	−2.60204
3.837553	12	0.555556	3.096539	0.180505	104.8422	4.235695	1.954844	4.840738	4.365997
8.026789	3.153153	−38.2979	−0.48019	−3.31665	24.50228	1.469885	7.116458	3.101737	3.051581
0.646907	4.897959	2.978723	1.052632	6.666667	31.63198	2.588235	−1.26441	3.665976	3.322476
2.347973	−6.57895	22.04181	0	−2.18978	80.98254	1.335159	0.540541	3.152188	0.844786
1.394879	4.385965	−5	2.631579	−2.5641	90.57967	12.49677	−3.12012	4.844774	2.125916
4.418718	16.59574	62.94643	−8.26893	7.476636	17.16852	2.029612	4.076308	10.46429	10.46429
1.315152	2.822581	1.968504	1.840753	1.051746	12.06555	−0.95444	0.612121	0.23819	−2.63143
1.025	−11.4754	−16.4063	−0.51869	−13.3964	48.77338	−6.76534	−5.55625	2.136396	−3.27951
7.859768	201.6949	−104.456	9.675908	4.823737	60.3613	5.613616	7.195363	4.239932	4.225752
16.33166	−518.251	15.58442	−3.71622	5.507246	160.739	−4.78469	8.626466	0.253539	−4.60596
0.168317	21.92536	26.54867	7.875648	9.002904	35.8354	−3.7912	−2.86139	1.71044	1.158987
1.508865	17.83652	−43.1349	0.270636	−3.07487	46.69917	−0.56264	−0.33949	1.66254	1.55642
2.146535	1.117318	2.212389	4.363905	3.050398	22.81446	3.052812	1.623762	0.744794	−0.532
5.456813	4.865051	10.67961	7.42488	4.49583	21.65618	−0.78375	4.313481	2.186047	1.465116
5.254622	20.98765	74.5098	11.11685	12.35834	16.20579	−0.86817	4.800519	2.834278	1.333778
7.721214	8.881923	20.62842	3.04878	10.21378	121.719	3.193165	4.47713	4.890076	4.420663
1.033121	1.290323	−0.81967	1.178203	0.618557	28.80735	2.547324	−1.58007	0.756558	−1.7818
1.519608	24.84472	21.05263	8.233506	8.549601	28.44933	3.785104	−0.22549	2.647546	2.279831
...	...	...	...	...	...	...	...	...	...

Table 2: Correlation of qualitative indicators of financial reports.

—	Dynamic price DayTop	Dynamic EPS	Dynamic EPS_0	Dynamic revenue	Dynamic $revenue_0$	Closeness W52	Dynamic PriceOpen	Dynamic price close	Dynamic price $DayTop_0$	Dynamic price $close_0$
Dynamic price DayTop	1	0.843226	−0.08701	0.895702	−0.04027	0.347455	0.144456	0.470492	0.086106	−0.02873
Dynamic EPS	0.843226	1	−0.0908	0.279679	−0.07154	−0.10439	0.212952	−0.04085	0.123416	0.190501
Dynamic EPS_0	−0.08701	−0.0908	1	0.024694	0.094496	0.008909	−0.10401	−0.1766	0.06312	0.012125
Dynamic revenue	0.895702	0.279679	0.024694	1	0.19	0.125214	0.301241	−0.29614	−0.06832	−0.06025
Dynamic $revenue_0$	−0.04027	−0.07154	0.094496	0.19	1	−0.04095	0.017823	0.014371	0.126041	0.099206
Closeness W52	0.347455	−0.10439	0.008909	0.125214	−0.04095	1	0.258216	−0.37856	0.224533	0.070996
Dynamic PriceOpen	0.144456	0.212952	−0.10401	0.301241	0.017823	0.258216	1	−0.06693	0.18579	0.213611
Dynamic PriceClose	0.470492	−0.04085	−0.1766	−0.29614	0.014371	−0.37856	−0.06693	1	−0.10715	−0.03182
Dynamic price $DayTop_0$	0.086106	0.123416	0.06312	−0.06832	0.126041	0.224533	0.18579	−0.10715	1	0.804337
Dynamic $PriceClose_0$	−0.02873	0.190501	0.012125	−0.06025	0.099206	0.070996	0.213611	−0.03182	0.804337	1

Table 3: Fragment of qualitative indicators of financial reports.

DynamicEPS	DynamicRevenue	ClosenessW52	DynamicPrice
0.209877	0.111168	0.016206	0.052546
0.088819	0.030488	0.121719	0.077212
0.012903	0.011782	0.028807	0.010331
...	...	...	...

Training Results

Training finished: Reached maximum mu

Training Progress

Unit	Initial Value	Stopped Value	Target Value
Epoch	0	242	1000
Elapsed Time	-	00:00:05	-
Performance	482	6.87	0
Gradient	2.69e+03	0.447	1e-07
Mu	0.005	5e+10	1e+10
Effective # Param	401	8.01	0
Sum Squared Param	3.93e+03	10.8	0

Figure 3: Training results.

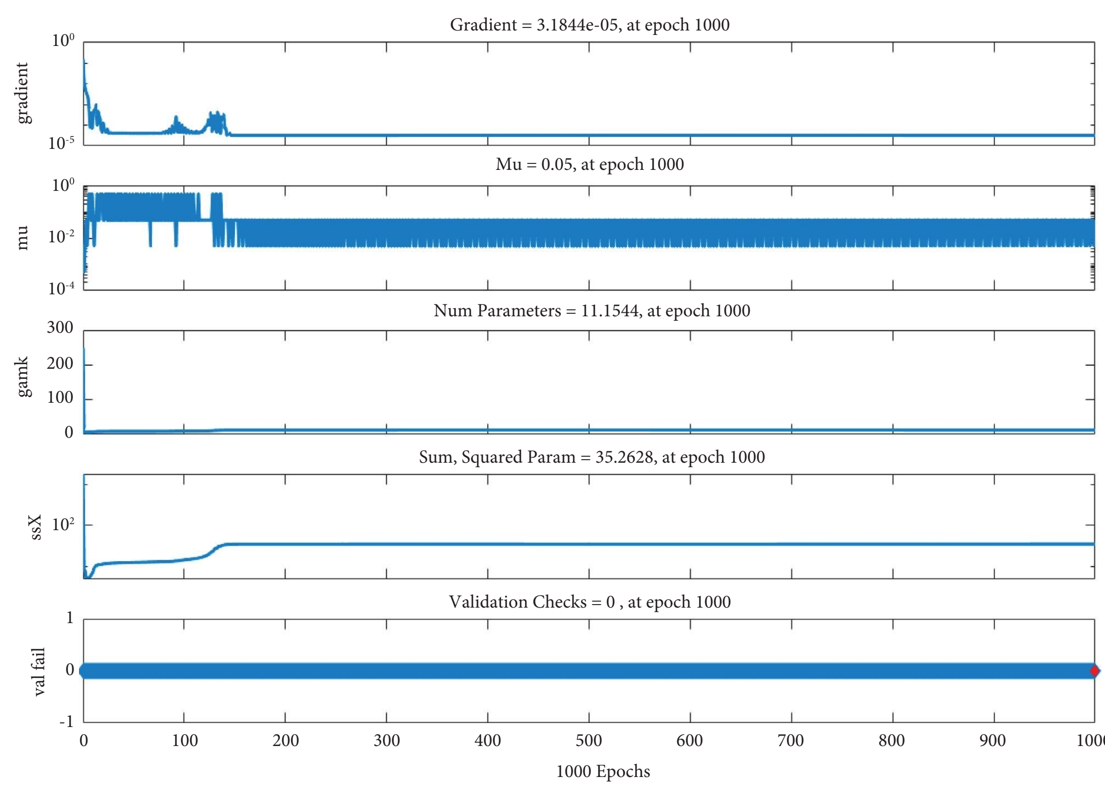

Figure 4: Graphs of training states.

Using ANFIS indicators, we make an assumption that if the output indicator is greater than 5%, then when buying a stock at the opening price, there is a good chance of getting 5% of the income when selling during the trading day. Next, we described the algorithm of the buying and selling process. Figure 12 and Table 5 describe a number of experiments that we conducted to prove our hypothesis. Tickers of companies that submitted financial reports were taken in the order of

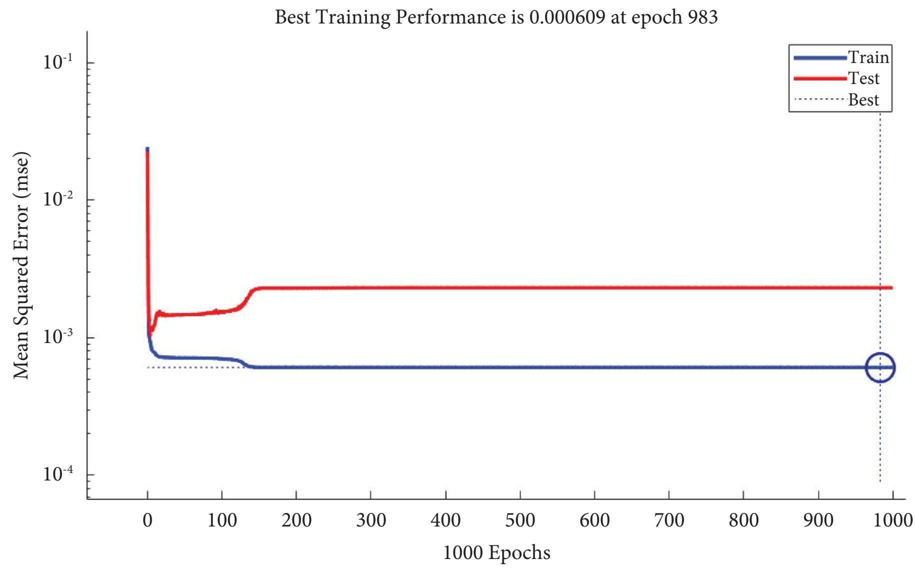

Figure 5: Graph of the best training performance indicator.

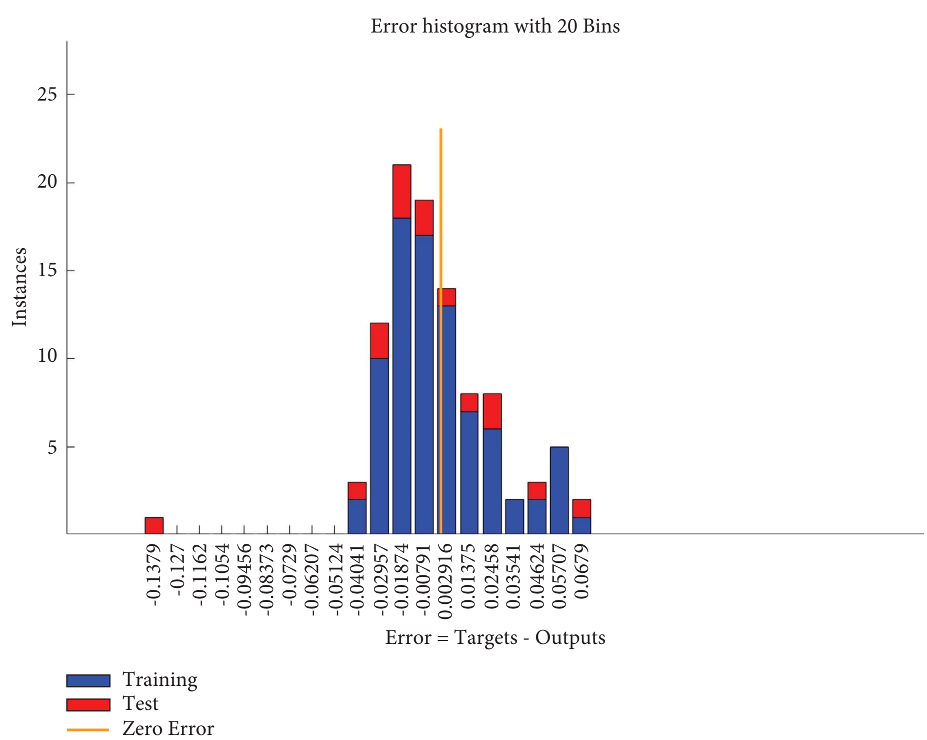

Figure 6: Error histogram chart.

the calendar list of reports from the finance Yahoo website. The data were collected until ANFIS received 4 values greater than 5%.

```
//function to get first trading price.
fixOpenPrice()
makeBuyOrder(ticker, openPrice, quantity)
timerUntil 11.30 a.m. ET.
checkStatus(buyOrder)
if (buyOrder = complete)
  then makeSellOrder(ticker, openPrice*5%, quantity)
  timerUntil 15.30 p.m. ET.
    checkStatus(sellOrder)
if (sellOrder = complete) Quit.
else deleteSellOrder(Id)
  makeSellOrder(ticker, openPrice, quantity)
```

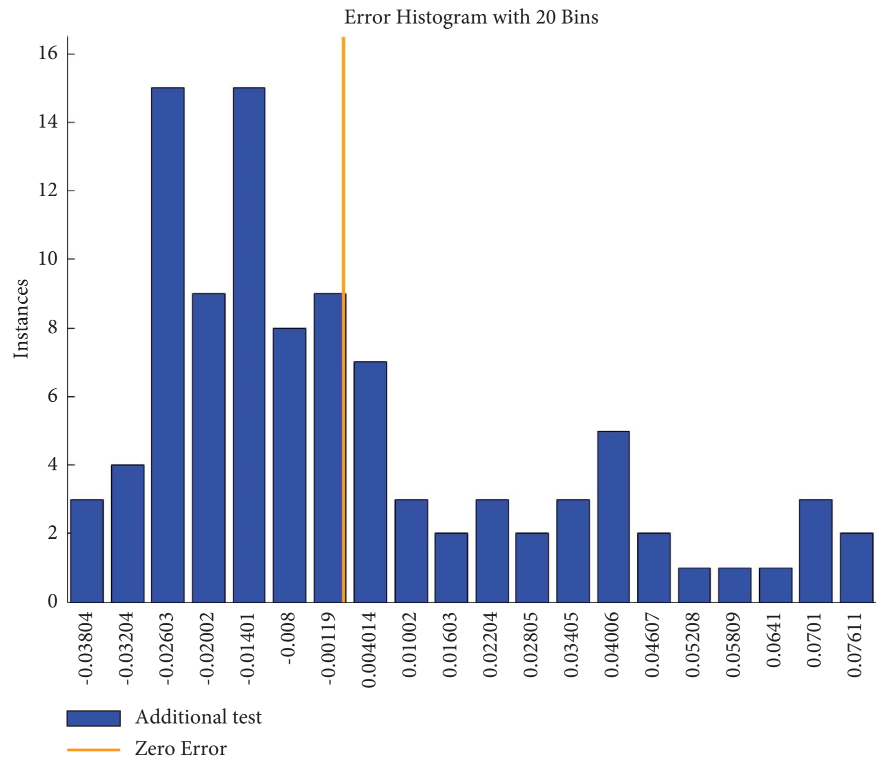

Figure 7: Test error histogram chart.

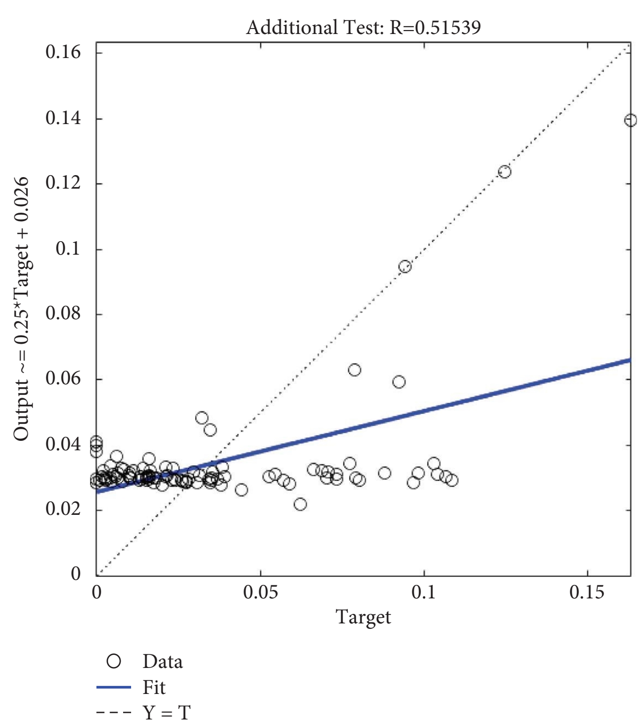

Figure 8: Testing regression chart.

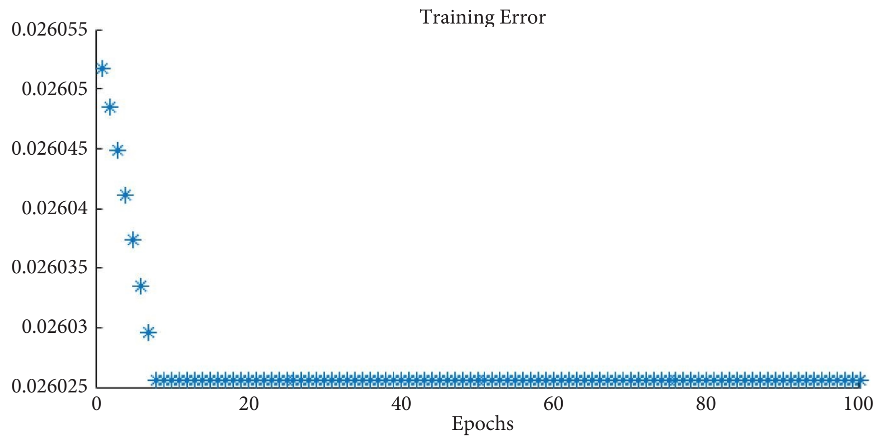

Figure 9: Minimum root mean square error of training.

Figure 10: Generated neurofuzzy model.

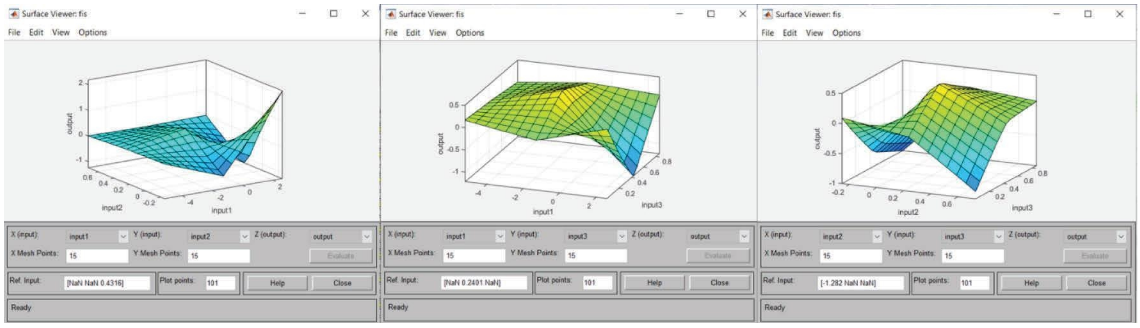

Figure 11: Models of surfaces of input and output variables.

Table 4: ANFIS forecast indicators.

Results of price change	ANFIS
0.163317	0.163316
0.124464	0.126818
0.093966	0.124463
0.092377	0.116382
0.078598	0.128356
0.058782	0.059691
0.09654	0.056185
. . .	. . .
0.009828	0.009828
0.016146	0.008736
0	3.24E-05

```
//after 11.30 a.m. ET.
deleteBuyOrder(Id)
```

A comparison of the training results of the proposed model with other works is described in Table 6 and Figure 13.

The proposed model has the lowest MSE and RMSE values, indicating better performance compared to the other models. Some models using optimization algorithms such as particle swarm optimization, firefly algorithm, genetic algorithm, and cat swarm optimization show competitive results. Traditional convolutional neural networks without denoising exhibit higher MSE and RMSE compared to other models. The table provides a comprehensive overview of model performances, with the proposed model standing out as particularly effective in minimizing prediction errors.

The proposed model stands out with the lowest MSE and RMSE values, indicating superior performance compared to the other models listed. GA-LSTM, DE-FLANN, GA-RBF, CSO-ARMA, PSO-ELMAN, PSO-MLP, BBO-MLP, and CSO-MLP also exhibit low MSE and RMSE values, suggesting competitive performance. SVM and BPNN show higher MSE and RMSE values, indicating comparatively less accurate predictions in the context of the given application. The provided figure offers a clear overview of the comparative performance of the proposed ANFIS model against various other models, highlighting its superior effectiveness in reducing prediction errors.

5. Discussion of Experimental Results

To support article's hypothesis, the study conducted several experiments, as illustrated in Figure 12 and described in Table 5. These experiments aimed to validate the assumption by analyzing the performance of different tickers of companies that submitted financial reports. The results of the study generally show that our main hypothesis about how earning reports affect investor sentiment is correct; it has been proven that there is a correlation between the data of the financial report and the behavior of the stock price. Research also proves that it is possible to predict the price movement based on data from earning reports for monetary gain. The study showed that the most important parameters in the reports are the dynamics of EPS, revenue, and MaxW52 with analysts' expectations. The main novelty lies in the fact that we used additional indicators, while researchers usually use only time series of price dynamics to train neural networks. It was also discovered that last year, the opening price of trading and the closing price of trading were strongly correlated with each other. These indicators are explained by the fact that 2021 was a good year in economic terms for many companies; many companies were on the rise after the lifting of restrictive measures in connection with COVID-19. It also indicates the absence of strong volatility during one trading day in 2021. And in 2022, companies are increasingly experiencing both a sharp rise in price and a sharp drop in price during one trading day. It has also been discovered that to a small extent, the closing price is negatively correlated with the yearly high price. That is, it can be concluded that if a company has submitted a bad report but the current price of the company is far from the price of a yearly maximum, then the drop will be minimal, and vice versa, if a company has submitted a bad report and is close to the price of a yearly maximum, then drop will be maximum. Moreover, if the company has submitted a good report but the current price of the company is far from the price of the yearly high price, then the growth will be maximum, and vice versa, if the company has submitted a good report and is close to the price of the yearly high price, then the growth will be minimal. The discovery for us was that the biotechnology company Veru Inc. (VERU) on December 5, 2022, submitted a very abnormally negative report and most likely, the price should

Industry:	ticker	Market Cap	avg volume	MaxW52	date	EPS	Analytic EPS	Dynamic EPS	Revenue	Analytic Revenue	Dynamic Revenue	Price Before Open	Closeness W52	Price Open	Dynamic Price Open	Price DayTop	Dynamic Price DayTop	Price Close	Dynamic PriceClose
Information Technology Services	SAIC	6.146B	359,333	113.03	Dec 05, 2022	1.9	1.74	9.195402	1.91	1.87	2.139037	109.26	3.4504851	112.9	3.331503	117.94	4.464128	113.96	0.93888397
Biotechnology	LEGN	9.19B	698,604	57.67	Dec 06, 2022	-0.1	-0.15	33.33333	113	106.04	6.563561	38.33	50.456561	43.85	14.40125	44.77	2.098062	41.95	-4.3329532
Software—Infrastructure	SUMO	909.255M	1,084,324	15.85	Dec 06, 2022	-0.04	-0.15	73.33333	79	74.21	6.454656	7.21	119.83356	7.9	9.570042	8.54	8.101266	8.07	2.15189873
Biotechnology	VERU	449.071M	5,127,146	24.55	Dec 05, 2022	-0.51	-0.3025	-68.595	2.59	11.55	-77.5758	5.5	346.36364	5.4	-1.81818	6.53	20.92593	5.82	7.77777778
Medical Devices	ICCM	38.336M	608,719	3.9	Dec 05, 2022	-0.11	-0.115	4.347826	634	908	-30.1762	1.07	264.48598	1.1	2.803738	1.1	0	1.035	-5.9090909
Biotechnology	CDMO	810.664M	663,996	31.01	Dec 07, 2022	-0.0057	0.0075	-176	34.76	32.05	8.455538	14.88	108.40054	13.28	-10.7527	13.3	0.150602	13.04	-1.8072289
Specialty Retail	AZO	46.604B	163,760	2610.05	Dec 06, 2022	27.45	25.26	8.669834	4	3.86	3.626943	2526.92	3.2897757	2441	-3.40019	2499.5	2.396559	2456.92	0.65219172
Aerospace & Defense	AVAV	2.072B	214,341	114.11	Dec 07, 2022	0	0.2	-100	111.58	113.43	-1.63096	85.11	34.073552	88.61	4.112325	88.61	0	82.37	-7.0420946
Entertainment	PLAY	1.616B	1,081,877	52.53	Dec 07, 2022	0.04	0.04	0	481.2	473.6	1.60473	36.2	45.110497	34.78	-3.92265	36.2	4.082806	33.51	-3.6515239
Aerospace & Defense	SWBI	434.401M	778,749	18.94	Dec 07, 2022	0.26	0.44	-40.9091	121	159.93	-24.3419	11.8	60.508475	10.82	-8.30508	10.82	0	9.49	-12.292052
Residential Construction	TOL	5.61B	1,744,195	75.61	Dec 07, 2022	5.63	3.99	41.10276	3.71	3.18	16.66667	45.94	64.58424	47.36	3.090988	49.81	5.173142	49.5	4.51858108
Software—Application	GWRE	4.943B	1,100,090	118.66	Dec 07, 2022	-0.12	-0.39	-69.2308	195.3	191.82	1.814201	56.52	109.94338	56.15	-0.65464	60.66	8.032057	60.37	7.51558326

Figure 12: Experimental data of calculating financial indicators.

Table 5: ANFIS forecast experiments.

Dynamic EPS	Dynamic revenue	Dynamic PriceDayTop	Dynamic PriceClose	Closeness W52	ANFIS	Profit
0.09195402	0.02139037	0.04464128	0.0093888397	0.0034504851	0.0310	—
0.3333333	0.06563561	0.02098062	−0.043329532	0.050456561	0.0434	—
0.7333333	0.06454656	0.08101266	0.0215189873	0.11983356	0.0547	5%
−0.68595	−0.775758	0.2092593	0.0777777778	0.34636364	0.0817	5%
0.04347826	−0.301762	0	−0.059090909	0.26448598	−0.0169	—
−1.76	0.08455538	0.00150602	−0.018072289	0.10840054	−0.0088	—
0.08669834	0.03626943	0.02396559	0.0065219172	0.0032897757	0.0294	—
−1	−0.0163096	0	−0.070420946	0.034073552	0.0087	—
0	0.0160473	0.04082806	−0.036515239	0.045110497	0.0272	—
−0.409091	−0.243419	0	−0.12292052	0.060508475	0.0217	—
0.4110276	0.1666667	0.05173142	0.0451858108	0.06458424	0.0525	5%
0.692308	0.01814201	0.08032057	0.0751558326	0.10994338	0.0603	5%

Table 6: Comparison of ANFIS with other well-known models.

Model	MSE	RMSE
Proposed model	0.000609	0.026026
Random search: convolutional neural networks [46]	314.9	17.7
Particle swarm optimization: convolutional neural networks [46]	194.5	13.9
Firefly algorithm: convolutional neural networks [46]	179.9	13.4
Modified firefly algorithm: multichannel convolutional neural network [46]	120.9	10.9
Genetic algorithm: long short-term memory [47]	0.007	0.089
Differential evolution: functional link artificial neural network [47]	0.009	0.03
Genetic algorithm: radial basis function [47]	0.003	0.056
Cat swarm optimization: auto regressive moving average [47]	0.001	0.038
Particle swarm optimization: ELMAN [47]	0.004	0.07
Particle swarm optimization: multilayer perceptron [47]	0.002	0.052
Biogeography-based optimization: multilayer perceptron [47]	0.001	0.043
Cat swarm optimization: multilayer perceptron [47]	0.0008	0.029
Gated recurrent unit based on complete ensemble empirical mode decomposition of adaptive noise: wavelet [48]	496.07	22.27
Long short-term memory [48]	693.79	26.34
Autoregressive integrated moving average [48]	769.68	27.74
Gated recurrent unit [48]	552.99	23.51
Convolutional neural network: bidirectional long short-term memory [48]	589.52	24.28
Support vector machine [49]	0.003	0.058
Back propagation neural network [49]	0.017	0.132
Traditional convolutional neural networks [50]	0.68	0.824666
Denoised traditional convolutional neural networks [50]	0.468	0.683787
Traditional convolutional neural networks LightGBM [50]	0.382	0.617769
Denoised traditional convolutional neural networks LightGBM [50]	0.215	0.463204
ResNet [50]	0.508	0.713024
Denoised ResNet [50]	0.424	0.65097
ResNet LightGBM [50]	0.365	0.603879
Denoised ResNet LightGBM [50]	0.156	0.395185

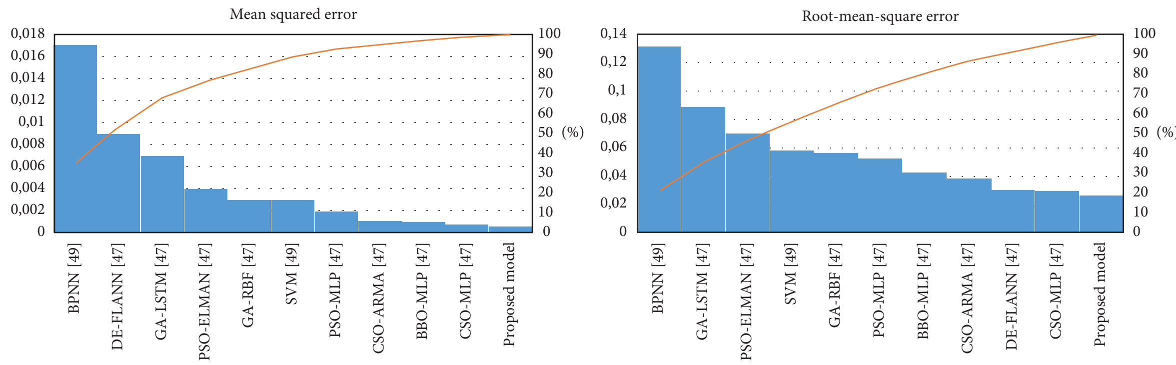

FIGURE 13: Pareto diagrams comparing MSE and RMSE models.

have collapsed at the opening of trading. It should be taken into account that MaxW52 was an abnormal 346.3636364%. ANFIS predicted growth at 8%, but in reality, this company grew at +20% during the trading day and by the end of the day, closed trading at +7.7% even with negative report data. After analyzing the sample on which the neural network was trained, we came to the conclusion that abnormal large negative indicators have a good effect on the emotional reaction of traders. It is also possible to build a hypothesis for further research that the report indicators are processed by computational algorithms, perhaps even AI, so it is necessary to investigate the emergence of the concept of emotionality of trading robots that are managed by investment funds. Having understood the behavior of algorithms, it becomes possible to get ahead of them and sell the purchased securities to these algorithms. Also, the results of the study include a scrapper, a sample of financial indicators, a neural network model, ANFIS, and an algorithm for buying and selling. In future work, we plan to compare our approach with other well-known machine learning models used in the evaluation of income statements.

6. Conclusions

First, an adaptive neurofuzzy system architecture was designed, providing a robust framework for the integration of neurofuzzy techniques and adaptive learning algorithms. This architecture facilitated the creation of a powerful tool for processing and analyzing financial data. In addition, the study focused on correlating qualitative indicators within financial statements to filter training data, ensuring that only relevant financial indicators were considered during the learning process. By identifying and prioritizing these qualitative indicators, the neurofuzzy system was optimized to generate more accurate and reliable interpretations of corporate earnings reports. Furthermore, a predictive experiment was conducted to validate the results of the study and to establish a solid foundation for the development of financial strategies. This experiment involved applying the trained neurofuzzy system to predict future financial trends and outcomes based on historical data. By successfully confirming the accuracy and effectiveness of the system through this experiment, it was demonstrated that the neurofuzzy system has the potential to aid decision-making processes and inform financial strategies in the corporate domain. Developed system showcases its ability to interpret complex corporate earnings reports, offering valuable insights to financial professionals and decision-makers.

Data Availability

The data used in this study, including company earnings reports and relevant financial data, were sourced from publicly available sources and databases. These sources primarily include reputable financial news websites (https://finance.yahoo.com/and https://www.investing.com/), official company websites, and regulatory filings such as 10-K and 10-Q reports filed with the U.S. Securities and Exchange Commission (SEC). The dataset is publicly accessible and does not contain any confidential or proprietary information. Researchers interested in accessing the data utilized in this study can refer to the aforementioned publicly available sources and databases. Specific details on the datasets used, including the names of companies, publication dates, and any unique identifiers associated with the data, are provided in the Methods section of this article for clarity and reproducibility. The developed neurofuzzy system's architecture, methodology, and implementation details are also described comprehensively to facilitate replication and verification of the results. For any inquiries regarding the data used in this study or further clarification on its availability, interested parties may contact the corresponding author.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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