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Stock Market Forecasting Using a Neural Network Through Fundamental Indicators, Technical Indicators and Market Sentiment Analysis

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Abstract
The objective of this research is to provide evidence that it is possible to obtain a prediction that better aligns with the future performance of a stock if a neural network model is trained with stock market analysis variables and qualitative variables. As a case study, thirty-three companies' representative of the S&P 500 are selected, and a multilayer perceptron artificial neural network is built and trained with input parameter indicators of fundamental analysis, technical analysis, and market sentiment. By incorporating the latter as an additional variable, the model's accuracy increases by 1.5% for 66% of the companies analyzed. The results confirm the crucial role played by the selection of the neural network model and its variables depending on the type of company to be analyzed. The main contributions of this research are the identification of the best variables combination to train a neural network model depending on the market sector to be analyzed, likewise it is demonstrated that, by using market sentiment, it is possible obtain a high accuracy or increase the accuracy to an existing model.

Keywords Stock market · Neural network · Market sentiment · Portfolio management · Investment decisions · Artificial intelligence

JEL Classification D71 · G11 · G12 · G17

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1 Introduction

An investment can be defined as the use of resources in the productive or capital sector with the objective of yielding benefits or profits. Currently, many investment instruments exist; however, one has attracted the interest of academics and investors over many years: The purchase and sale of shares on stock exchanges.

Due to the crucial number of quantitative and qualitative variables involved, every decision maker in the stock market faces the possibility of volatility in the financial markets. As a result, having adequate planning and, therefore, a solid investment strategy is crucial, as are analysis tools and models that allow decision-makers to process significant amounts of information to better understand the market and to update their investment strategies.

In recent years, globalization and technological progress have yielded evolutions in all fields of study, and the financial environment was no exception, technological progress has revolutionized the field of finance in three principal ways.

According to Belton (2021), Technology has made it possible to bring the stock market closer to investors through online platforms that facilitate the purchase and sale of investment instruments.

In addition, technological progress has ushered in a new era of data processing tools with the use of artificial intelligence and machine learning models for financial decision making; and has also enabled access to real-time information on any topic.

Sarmiento (2017) states that the proliferation of news and social networks has generated new sources of information using millions of data points from users worldwide, and Gurdgiev (2020) argues that these data points influence decision makers in the stock market. As a result, every decision-maker in the stock market environment must now be attentive to the news and content that is distributed by social networks because, as Pardo (2021) states, this information impacts the prices of financial instruments regardless of whether it is truthful.

Therefore, in this research, we want to use these new tools to illustrate that obtaining a forecast more closely aligned with the future performance of a stock is possible by involving variables of stock market analysis and qualitative data such as market sentiment in a multilayer perceptron artificial neural network programmed in the web solution Azure Machine Learning Studio.

The main contributions are the identification of the best variables combinations to train a neural network model depending on the market sector to be analyzed. Likewise, the research allows understanding of the behavior of thirty-three representative stocks of the S&P 500, the relationships between them and the opinions about them on social networks. Additionally, it is demonstrated that, by using market sentiment, it is possible obtain a high accuracy or increase the accuracy to an existing model.

The results confirm the hypothesis that creating a machine learning model that involves variables of stock analysis and qualitative data such as market sentiment can yield forecasts that are presumably closer to the future performances of stocks since of 11 sectors, 7 of them have the highest value of the coefficient of determination in the models in which market sentiment was included.

Thus concluding that the use of new technologies, such as artificial intelligence, enables a significant amount of information to be accurately and quickly analyzed, reducing the reaction time and aiding the decision-making process.

The article is structured as follows, first an introduction is presented where the context and relevance of the study is established, together with the main objectives, hypotheses, and contribution. Next, the existing literature is summarized, providing a critical analysis of previous research. In Methodical background section the basis for the construction of the proposed model is presented. The topics include the main definitions of the S&P 500 Index; and market sentiment and artificial intelligence, which are two topics that have emerged in recent years and are fundamental parts of this proposal. On the Methodical approach section the scope; data sources and preprocessing steps to prepare the data; and the definition, construction and training of the algorithm was presented. Subsequently, on Results and discussion section, the findings of the study are presented and an analysis and interpretation of them is made. Finally, the conclusion summarizes the key points of the study, its limitations and proposes future lines of research.

2 Related Work

The following is a brief presentation of the research work, as well as suggestions from experts related to the resolution of the described problems.

2.1 Sentiment Analysis in Stock Market Prediction

Sentiment analysis in stock market prediction is an emerging field that combines natural language processing and financial analysis to provide valuable insights into market trends and investor behavior. Below is a summary of the research related to this topic.

Studies by Alsing and Bahceci (2015), Rajesh (2016), Sarmiento (2017), Zhao and Yang (2023), Lee et al. (2024), Shah et al. (2024), Shankar et al. (2024), Gupta and Chen (2020), Madoery (2021) and Javed Awan et al. (2021) focus on sentiment analysis from social media or news to predict stock prices or market movements. These studies explore the relationship between public sentiment and stock market behavior.

Alsing and Bahceci (2015) and Bannister (2021) state that sentiment analysis (SA), machine learning (ML), and data mining (DM) have recently become popular techniques for analyzing public emotion (market sentiment) to predict stock prices. Through their research, they conclude *"There is a weak relationship between a company's stocks and their respective social media posts, so we do not recommend it as a standalone analysis. However, it can be used as a supplement that could add accuracy to an existing model" (Alsing and Bahceci,* 2015*).*

Rajesh (2016) uses a CashTagNN system that uses sentiment and subjectivity scores of tweets including cash tags of two companies to model the movement of these investment instruments in the stock market and predict opening and closing prices. He concludes that *"It is demonstrated that, by using sentiment and subjectivity along with a neural network learning model, it is possible to predict the opening and closing prices of the two companies with high precision"* (Rajesh, 2016).

Sarmiento (2017) emphasizes the importance of information and communication technologies in the financial sector. His work focuses on building a data model to classify tweets to identify opinion trends on the social network Twitter related to stock market behavior. He concludes that a data analysis model that relates social network trends to stock market behavior is an important tool for the financial sector, as it provides decision-makers with a real-time perspective on the opinions of Internet users.

Zhao and Yang (2023) reaffirm that investor emotion is an important factor in the financial market, which is reflected in the opinions of social networks. They confirm that detecting the sentiment of stock market messages is challenging, but if an effective method is used to extract this knowledge, investor sentiment can be calculated, enabling the construction of sentiment indexes that more effectively forecast the movements of stocks when combined with stock market data, prompting every stock market decision maker to make efficient investment decisions.

Lee et al. (2024) proposes an approach that combines ESG sentiment index extracted from news with technical indicators to predict the S&P 500 index. The results demonstrate improved predictive accuracy when considering ESG sentiment compared to relying solely on technical indicators or historical data, but they confirm the findings may not comprehensively represent the dynamics of the entire financial market, therefore they propose that future research could attempt to predict stocks by industry group.

Shah et al. (2024) and Gorbatenko (2021) explores the link between public opinion and stock market dynamics, highlighting the role of social and web-based media as key indicators of public sentiment. Methods for efficiently processing large datasets from online platforms using big data analytics and sentiment insights to improve market predictions and forecast stock market trends are reviewed.

Finally, Shankar et al. (2024) developed a model that combines long short-term memory (LSTM) to capture dependencies, the autoregressive integrated moving average (ARIMA) strength in modeling linear relationships, and sentiment analysis of public sentiment from Twitter data. Results show that proposed model outperforms individual models, improving prediction accuracy and finds a strong correlation between stock price movements and public sentiment.

2.2 Use of Machine Learning in Stock Market Prediction

The utilization of machine learning in stock market prediction represents a groundbreaking advancement in financial technology. By leveraging sophisticated algorithms and large datasets, machine learning models can identify complex patterns and trends in a short period of time. Below is a summary of the research works related to the development of machine learning models for stock market prediction.

Gálvez (2016), Peng and Jiang (2016), Ordóñez (2017), Hung et al. (2024) and Oyewole et al. (2024) utilize machine learning techniques, including neural networks, to predict stock prices or trends. They demonstrate the effectiveness of these techniques in improving prediction accuracy compared to traditional methods.

First, Gálvez (2016) suggests that it is possible to extract information that contains predictive power on the daily performance of a series of stocks traded in the Buenos Aires Stock Market (Merval) through analyzing the interactions of individuals within an online stock forum in Argentina. He confirms that *"when this information is incorporated into traditional machine learning systems aimed at predicting the direction of daily stock performance, their performance improves"* (Gálvez, 2016).

Peng and Jiang (2016) claim that financial news contains useful information about public companies and the market. In their work, they apply popular word embedding methods and deep neural networks to predict stock price movements in the market through financial news, stating that "*Our proposed method is simple but effective, which can significantly improve the accuracy of asset prediction in a financial database on the baseline system using only historical price information (Peng & Jiang, 2016).*

Ordóñez (2017) studies the use of neural networks in conjunction with technical analysis to forecast the trend and the value that the closing price of an asset will have in a given period. He concludes that if additional indicators are incorporated in the study of stock market behavior, the analysis can be strengthened, and the prediction accuracy can be improved.

Hung et al. (2024) utilize deep learning and natural language processing to construct view distributions in the Black–Litterman model for portfolio allocation. It finds that the GRU model outperforms LSTM and RNN models in predicting stock prices. Additionally, the Black–Litterman model, using BERT for sentiment analysis and GRU for price prediction, achieves the highest annualized return rate of 46.6% and superior Sharpe and Sortino ratios of 13.0% and 17.9%, indicating better performance under risk compared to other portfolio models.

Oyewole et al. (2024) explores the potential of neural network models for stock market prediction, comparing their performance with traditional models. It emphasizes the importance of data preprocessing and highlights neural networks' superior ability to capture complex market patterns and adapt to volatility. The study underscores the critical role of data quality, neural network architecture, and strategic implications for investors.

On the other hand, Huang et al. (2021) focus on using machine learning algorithms to analyze financial data for stock prediction based on fundamental analysis. They trained three machine learning algorithms: Feed-forward Neural Network (FNN), Random Forest (RF) and Adaptive Neural Fuzzy Inference System (ANFIS) with 22 years of quarterly stock financial data for stock prediction based on fundamental analysis. They demonstrated that machine learning models could be used to assist fundamental analysts in decision-making regarding stock investment.

2.3 Applications of Machine Learning in Finance

Nowadays artificial intelligence has become an indispensable tool for banks and financial institutions. Leveraging these technologies, the organizations are enhancing their capabilities in risk management, fraud prevention, and financial advisory services. “An example is Paypal, through deep learning, has been able to increase security by decreasing its fraud to 0.32% of revenue” (Lin, 2021). Below is a summary of the principal applications and uses of artificial intelligence models in the financial sector.

In general, Mittal et al. (2019) and Kour (2024) explore the transformative impact of big data and machine learning on finance, highlighting their applications in finance areas. Mittal et al. (2019) present a comprehensive review of big data and machine learning techniques. It discusses the applications of these techniques in various domains, including finance. Kour (2024) examines how machine learning is revolutionizing data analysis, decision-making, and risk management in finance. It discusses its applications in stock market forecasting, credit risk assessment, fraud detection and portfolio optimization, including challenges such as model robustness, interpretability, data quality, and regulatory compliance persist.

Kumar et al. (2024), Owusu and Gupta (2024), Yu and Zhao (2020), Kumar et al. (2018), Musa et al. (2024), Diwanji et al. (2023) and Somanathan pillai et al. (2024) highlight the importance of machine learning in enhancing the prediction and management of systemic risk and fraud prevention in financial and banking sector.

For risk management, Kumar et al. (2024) and Yu and Zhao (2020) analyzed the systemic risk of Indian banks, Kumar et al. (2024) applied machine learning models to identify balance sheet and stock features that determine systemic risk. The findings indicate that random forest and gradient boosting machine are the preferred models, highlighting stock beta, stock volatility, and return on equity as key factors in systemic risk emission. Likewise, Yu and Zhao (2020) identified if institutions have sufficient capital reserves to prevent risk contagion using logistic regression and random forest models, improving the accuracy of risk prediction models.

Owusu and Gupta (2024) developed an unsupervised machine learning approach to identify significant features for assessing and differentiating risk culture in banks. They utilized unstructured text from banks and a K-means clustering to group the reports into distinct risk culture categories. The findings indicate that good and fair risk cultures are associated with high profitability, bank stability, lower default risk, and good governance.

For fraud prevention, Kumar et al. (2018) utilized account-level transaction data to predict suspicious activities related to external financial fraud. They employed logistic regression, random forest, and support vector machine learning techniques to enhance the detection of alerts within a proprietary transaction monitoring system, achieving a new alert model with high predictive accuracy.

Musa et al. (2024) and Diwanji et al. (2023) tackle the increasing problem of credit card fraud on online payments and e-commerce areas. They demonstrate the use of machine learning for credit card fraud detection.

Somanathan pillai et al. (2024) developed a model to address repeated loan fraud. They used machine learning models, automating data preprocessing with KNN and employing a 1DCNN for classification achieving 98.62% accuracy, outperforming other methods. Their approach offers a faster, more precise fraud detection method for lending banking.

For financial advice Lin (2021) states robo-advisors are digital platforms that provide automated financial planning services based on algorithms with minimal supervision by humans, so they can offer investors up to 70% in cost savings. Today they are used for account opening and asset transfer. Xue et al. (2018) introduces an incremental multiple kernel extreme learning machine (IMK-ELM) model for Robo-advisors, addressing the challenge of information fusion in heterogeneous data. The IMK-ELM model updates both the training dataset and the weights used to combine multiple information sources, demonstrating its effectiveness in solving classification problems and efficiently handling large-scale tasks.

In summary, the applications of machine learning in finance are extensive and continuously expanding. From fraud detection and risk management to algorithmic trading and customer service, machine learning algorithms are transforming the industry. These technologies offer the potential to enhance decision-making, increase efficiency, and improve customer experience.

This research highlight the diverse applications of machine learning, sentiment analysis, and data analysis in predicting stock prices and market trends, providing valuable insights for decision-makers in the financial sector. The extent to which market sentiment affects stock behavior remains debatable. Nevertheless, it is undeniable that this factor should not be overlooked.

Based on the problems and the review of related work, it is concluded that, although a significant number of articles and scientific publications propose methods for forecasting a stock's performance or behavior over time, no proposals were found during the literature review that incorporate technical analysis, fundamental analysis, and, most importantly, market sentiment in the same model.

3 Methodical Background

In this section, the basis for the construction of the proposed model is presented. The topics are separated into the following sections: S&P 500 Index, where the main definitions of this Index are addressed; and market sentiment and artificial intelligence, which are two topics that have emerged in recent years and are fundamental parts of this proposal.

3.1 S&P 500 Index

A stock market index (stock index) "is an indicator that shows the variation in the price of a set of listed assets that meet certain characteristics" (Castro, 2021). Currently, the S&P 500 is considered a representative index of the real market situation due to its stability and continuity over time, its broad acceptance among investors and financial analysts, its transparency in the calculation methodology, and its long-term performance history, making it a reliable and consistent indicator. It includes the 500 largest companies worldwide and encompasses 11 sectors, as shown in Fig. 1.

Companies included in the S&P 500 are selected by the S&P Dow Jones Indices Index Committee. To qualify, a company must meet specific criteria. Firstly, it must have a minimum market capitalization, which fluctuates but generally amounts to

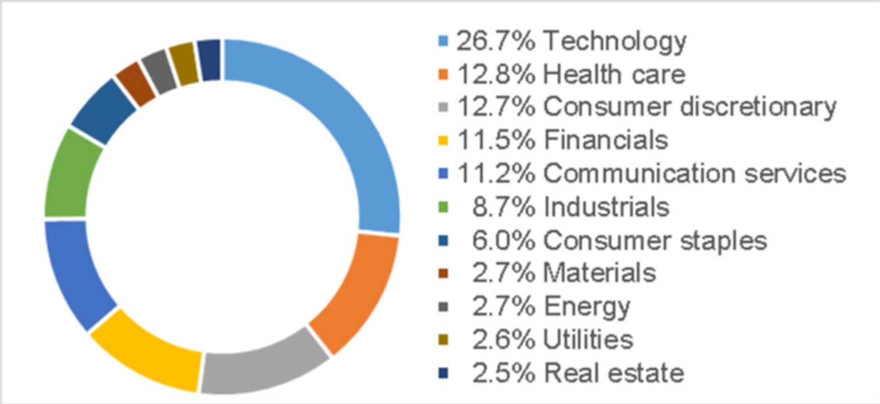

Fig. 1 Sectors of the S&P 500. *Source*: Prepared by author based on S&P Global (2021)

several billion dollars. Secondly, its shares must exhibit sufficient liquidity, indicating a minimum trading volume. Thirdly, the company must be headquartered in the United States. Additionally, an equitable representation across various sectors of the economy is sought. Lastly, the company's financial stability and profit history are among the factors considered for inclusion in the index.

3.2 Market Sentiment

Sentiment is a general thought, feeling or sense. Saettele (2017) states that in free markets, sentiment refers to the set of feelings and emotions of all market participants; in other words, "Market sentiment is the dominant emotional condition of participants with respect to the price direction. This indicator is often used to measure collective thinking" (Molina, 2021).

Alsing and Bahceci (2015) state that markets are sets of people acting with their own thoughts and their own conclusions. Market sentiment is constructed when these people, who operate in the markets, share their feelings about what is going to happen.

In contrast to fundamental and technical analysis, market sentiment analysis focuses on measuring the psychological and emotional states of market participants to obtain an overview of the optimism or pessimism prevailing at a given time and generate an additional indicator for investment decisions.

Currently, several methods for monitoring changes in market sentiment exist; however, research primarily focuses on measuring market sentiment using artificial intelligence models, such as machine learning and neural networks.

3.3 Artificial Intelligence

Based on the definition of Takeyas (2015), artificial intelligence (AI) is a branch of computational sciences which examines computational models capable of performing human activities based on two of their primary characteristics: reasoning and behavior.

AI currently has a presence in all areas of daily life. Vázquez (2020) subdivides AI in: Machine learning, probabilistic reasoning, and genetic algorithms.

3.3.1 Machine Learning

Machine learning is a subset of artificial intelligence that is defined as "the ability of machines to learn on their own by adjusting algorithms as they process information and gain knowledge about the environment" (Hurwitz & Kirsch, 2018). Its value lies in its ability to continuously learn from data using algorithms that detect certain patterns.

According to Hurwitz and Kirsch (2018), various types of machine learning models exist. In supervised learning, the algorithm is trained from data labeled with the correct answer, and once trained, it is able to predict outcomes when given new data. In unsupervised learning, the algorithm is trained on unlabeled data, and it learns to identify patterns that can help it understand the dataset. In reinforcement learning, the algorithm learns by trial and error until it can perform the task efficiently.

Deep learning, on the other hand, is a more complex type of machine learning inspired by the functioning of neural networks in the human brain. It uses different layers, which act as neurons, to process information. These layers enable deep learning models to learn a hierarchy of data representations, thus enabling them to solve complex problems (Nielsen, 2015) and Sherstinsky (2020).

3.3.2 Deep Learning

Deep learning is a subfield of machine learning that employs various neural network architectures to learn successive layers of increasingly meaningful data representations. An example of this is the neural network.

"A neural network consists of three or more layers: an input layer, one or more hidden layers, and an output layer," (Hurwitz and Kirsch, 2018). Data are fed into the input layer, and the weights applied to these nodes then modify the data in the hidden and output layers. A typical neural network can comprise thousands or even millions of densely interconnected simple processing nodes. The composition of a simple neuron in a neural network is presented in Fig. 2.

where:

$\boldsymbol{x}_1,\boldsymbol{x}_{2,\ldots,}\boldsymbol{x}_{\boldsymbol{n}}$ are the input data of the neuron, which can be products of the output of another neuron in the network.

$\boldsymbol{x}_0$ is the bias unit, which is a constant value that is added to the neuron's activation function input. This value allows the activation function to change, giving the neuron more flexibility to learn.

$\boldsymbol{w}_{0,}\boldsymbol{w}_{1,\ldots,}\boldsymbol{w}_{\boldsymbol{n}}$ are the relative weights of each input, where even the bias unit has weight.

a is the output of the neuron that is calculated with the following expression, where f is the activation function of the neuron. This function gives flexibility to

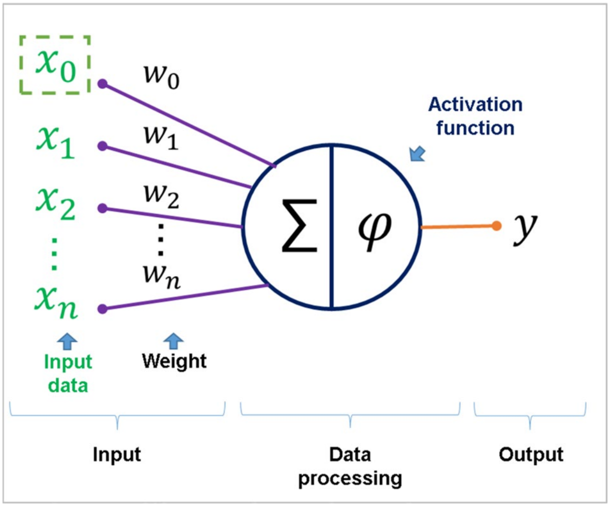

Fig. 2 Composition of a simple neuron. Source: Prepared by author based on Briega (2020)

neural networks and allows complex nonlinear relationships in the data to be estimated. It can be a linear function, a logistic function, a hyperbolic function, etc.

$$a = f\left(\sum_{i=0}^{n} w_i * x_i\right) \tag{1}$$

In this way, each neural unit is connected to numerous others, and the connections between them can strengthen or inhibit the activation state of neighboring neurons. These systems learn and train themselves rather than being explicitly programmed.

As stated by Nielsen (2015), the term "deep learning" is used when a neural network has multiple hidden layers. The general operation of deep learning models involves reducing the value of the loss function by processing new cases that enable the weights of each layer, which are initially assigned randomly, to be adjusted.

To control the output of the neural network, we must measure how much the obtained result (output) differs from the target value (expected). For this purpose, the network's loss function, which accounts for the predictions made by the model and the target values and calculates the degree of divergence from the target value, is utilized.

This process is referred to as network training, and a model is considered trained once the loss has been minimized; hence, the results are the ones that best fit the target value. However, a deep learning network can have millions of parameters.

Therefore, Goodfellow (2016) and Bagnato (2021) states that the fundamental trick of deep learning is to use the value returned by the loss function to feed back into the network and adjust the weights in the direction that reduces the loss of the model for each example. This adjustment is completed by the optimizer, which implements backpropagation.

4 Methodical Approach

To provide conclusive answers to the problem raised, an overview of the proposed multilayer perceptron artificial neural network created is presented here.

4.1 Scope

For the purpose of the case study, companies that form part of the S&P 500 were selected. The analysis considers only thirty-three of the five hundred companies that compose the S&P 500 due to the need for more robust software and infrastructure to process the data of all companies in this index.

To ensure a balanced representation across all sectors this case study was limited to three representative companies per sector, as shown in Table 1.

The selection process for the companies was based on the following criteria:

1. First, the operating volume of each company was considered. For instance, Altria Group, which operates at a volume of 8.065 M, is among the top five companies in the Consumer staples sector. Similarly, Boeing Company was ranked as one of the most important companies in the industrial sector, with a volume of 6.125 M.

Table 1 Companies to be analyzed per sector. *Source*: Prepared by author

Sector	Empresa	Sector	Empresa
Technology	Oracle (ORCL)	Consumer staples	CVS caremark (CVS)
	Apple Inc (AAPL)		Altria group (MO)
	Microsoft (MSFT)		Coca-cola company (KO)
Health care	Cigna (CIGNA)	Materials	DuPont (DD)
	Quest diagnostics (DGX)		Sherwin-Williams (SHW)
	Pfizer Inc. (PFE)		Newmont Corp (NEM)
Consumer discretionary	General motors (GM)	Energy	Pioneer natural resources (PXD)
	Home Depot (HD)		Chevron (CVX)
	Netflix Inc. (NFLX)		ExxonMobil (XOM)
Financials	Keycorp (KEY)	Utilities	Edison international (EIX)
	Wells Fargo (WFC)		NextEra energy (NEE)
	Berkshire Hathaway(BRK)		American electric power (AEP)
Communication services	AT&T (T)	Real estate	Simon property group (SPG)
	Disney (DIS)		Public storage (PSA)
	Meta platforms, Inc. (FB)		Prologis (PLD)
Industrials	Boeing (BA)		
	3 M (MMM)		
	General electric (GE)		

2. Second, historical performance was used as a criterion. For the Communication services sector, Verizon Communications and Activision Blizzard maintained significant operating volumes. However, their performances over the last year were not satisfactory, recording -4% and 3% annual performance, respectively. Disney, however, recorded a 20% performance during the same period of analysis.
3. Third, the investment experience of the chosen issuers was considered, given that the expertise of the person making the forecast plays a crucial role in the analysis.

For each selected stock, information was taken for the last five years (January 03, 2017 to November 04, 2021), including daily closing, opening, high, low, volume, historical reports of each company (financial summary, balance sheet, cash flow and income statement) and total positive sentiment and negative sentiment opinions.

All the information was extracted from the Investing website (2021), which provides stock market information and news such as charts, technical and fundamental indicators, and news and opinion forums of stock market decision makers.

Figure 3 shows the variables of interest that were incorporated into the multilayer perceptron artificial neural network.

Each set of indicators is calculated as follows:

- Fundamental Analysis: The data for the calculation of fundamental analysis have been extracted from the historical reports of each company (financial summary, balance sheet, cash flow statement, and income statement).
- Technical Analysis: The technical analysis was conducted using the daily closing, opening, high, and low prices as input. With these variables, the simple moving average, relative strength index and stochastic oscillator of each stock were calculated.
- Market Sentiment: The third type of variable was calculated based on the opinions of individuals within the investing social network. The total number of mentions during the period being analyzed was extracted, each opinion has a target price. If the target price was higher than the closing price of the current day, it is considered a positive sentiment; conversely, if the target price was lower than the closing price of the current day, it is considered a negative sentiment. Under this framework, the ratio between the total number of positive sentiment opinions

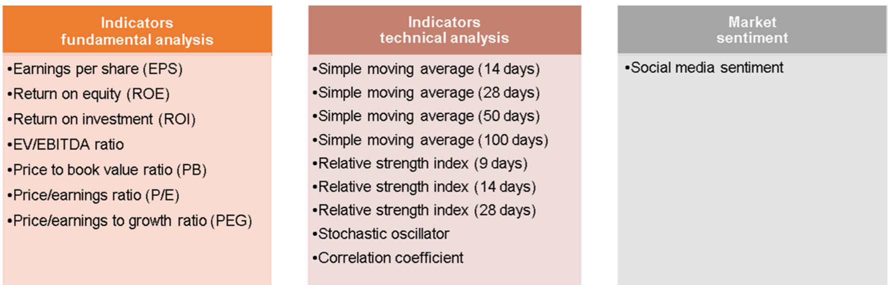

Fig. 3 Proposed variables of interest. *Source*: Prepared by author

vs. negative sentiment opinions (positive–negative ratio) was calculated. Sanz (2020) states that a value below 1.0 indicates a predominantly negative sentiment.

Finally, to train the neural network, the variation in the closing price and the closing price of the following day is calculated. The following criteria were established to represent the buy and sell signals:

- Place 1 if it is a Buy Signal: If the variation is positive, that is, the closing price of the following day is higher than the closing price of the analyzed day, it is determined that the variables of the analyzed day indicate a buy signal.
- Place -1 if it is a Sell Signal: If the variation is negative, that is, the closing price of the following day is lower than the closing price of the analyzed day, it is determined that the variables of the analyzed day indicate a sell signal.
- Place 0 if There is no Signal in That Period: If the variation is zero, that is, the closing price of the following day is equal to the closing price of the analyzed day, it is determined that the variables of the analyzed day do not indicate any signal.

For the development of the model, the Azure Machine Learning Studio web solution (free version) was used. This is a cloud service that allows for accelerating and managing the lifecycles of machine learning projects from open-source platforms such as PyTorch, TensorFlow, or Scikit-learn.

The methodology used for the definition, construction, and training of the algorithm follows the framework presented by Agarwal (2022), where the process for building a machine learning system can be summarized in five steps: problem definition, data collection and preprocessing, algorithm training, algorithm evaluation, and model utilization.

4.2 Machine learning Algorithm, Creation, and Training

Prior to programming the machine learning algorithm, data collection and preprocessing are conducted to ensure optimal data quantity and quality. During this phase, table unification is performed, and cleaning, labeling, standardization, and calculation of secondary variables derived from the primary data are conducted, leaving at the end of this phase more than 1,489,000 data in total (approximately 45,140 data for each company).

To select the machine learning algorithm, the definitions by Alsing and Bahceci (2015), Molina (2021), Saettele (2017), Liutvinavicîus et. al. (2017) and Shiller (2019) were considered. They affirm that markets move based on emotional and intuitive impulses, also called market sentiment, confirming that it is human psychology that drives markets in one direction or another. These findings from behavioral economics have led to the development of alternative approaches and models for decision making.

Considering the above and according to Pettersson and Falkman (2023) it was decided to use a multilayer perceptron artificial neural network because a key variable to be incorporated into the model is market sentiment, which represents human behavior.

A neural network is a computational model consist of three or more layers (an input layer, one or more hidden layers, and an output layer) that are fully connected. Each neuron receives inputs, performs a dot product, and then applies an activation function, finally applying a loss or cost function on the last layer. Therefore, to achieve an optimal model it is necessary to define multiple variables and parameters to create and train the neural network.

Based on the above, the model's input variables can be classified into:

- General: provide information about the stock prices of the selected companies, the variables used are shown in Table 2.
- Fundamental Analysis: variables derived from fundamental analysis indicators, the variables used are shown in Table 3.
- Technical Analysis: variables derived from technical analysis indicators, the variables used are shown in Table 4.
- Market Sentiment: variables that measure social media sentiment, the variables used are shown in Table 5.

To select the configuration parameters of the neural network, the Tune Model Hyperparameters module of the same web solution where the multilayer perceptron artificial neural network was developed (8+) is used. This module determines the optimal parameters for a machine learning model through the constructing, testing, and comparing multiple models with different combinations of configurations. Table 6 shows the parameters established for this research.

The variable to be estimated is the closing price of the stock for the following day. The percentages of data to be used for training and evaluation are 80% and 20%, respectively. For training purposes, six combinations of input variables are

Table 2 General input variables. *Source*: Prepared by author

Classification	Variable	Data type
General	Date	Date
	Closing price	Float
	Opening price	Float
	High price	Float
	Low price	Float
	Trading volume	Float
	Return	Float
	Next day closing price	Float
	Next day return	Float

Table 3 Fundamental analysis input variables. *Source*: Prepared by author

Classification	Variable	Data type
Fundamental Analysis	Price-to-book ratio (P/B)	Float
	Earnings per share (EPS)	Float
	Price-to-earnings ratio (P/E)	Float
	EV/EBITDA Ratio	Float
	Price/earnings to growth ratio (PEG)	Float
	Beta	Float
	Return on equity (ROE)	Float
	Return on assets (ROA)	Float
	Debt-to-equity ratio	Float

Table 4 Technical analysis input variables. *Source*: Prepared by author

Classification	Variable	Data type
Technical analysis	14-Day simple moving average signal	Float
	28-Day simple moving average signal	Float
	50-Day simple moving average signal	Float
	100-Day simple moving average signal	Float
	9-Day relative strength index (RSI) signal	Float
	14-Day relative strength index (RSI) signal	Float
	28-Day relative strength index (RSI) signal	Float
	Stochastic oscillator signal	Float

Table 5 Market sentiment input variables. *Source*: Prepared by author

Classification	Variable	Data type
Market sentiment	Social media sentiment strength	Float
	Number of social media mentions	Float

Table 6 Configuration parameters. *Source*: Prepared by author

#	Parameter	Definition	Value
1	Architecture	Neural network selected to be developed	Multilayer perceptron neural network
2	Hidden nodes	Number of hidden layers of the model	100
3	Learning rate	Step size in each iteration before correction	0.01
4	Learning iterations	Maximum number of times the algorithm should process the training cases	24
5	Initial learning weights	Weights of the nodes at the beginning of the learning process	0.1
6	Random examples	Allows mixing cases between iterations	False

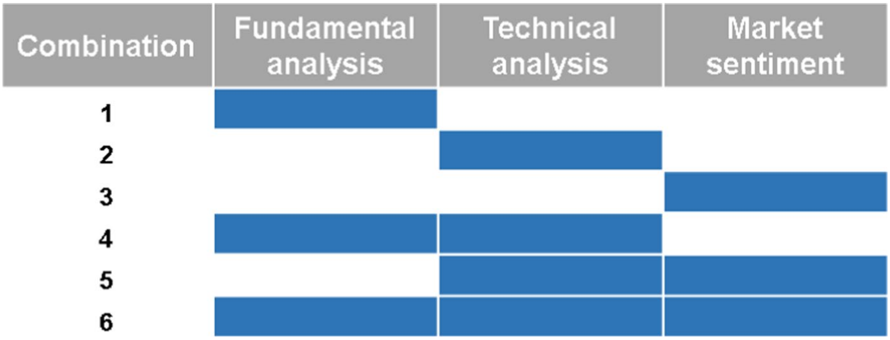

Fig. 4 Combinations of input variables, *Source*: Prepared by author

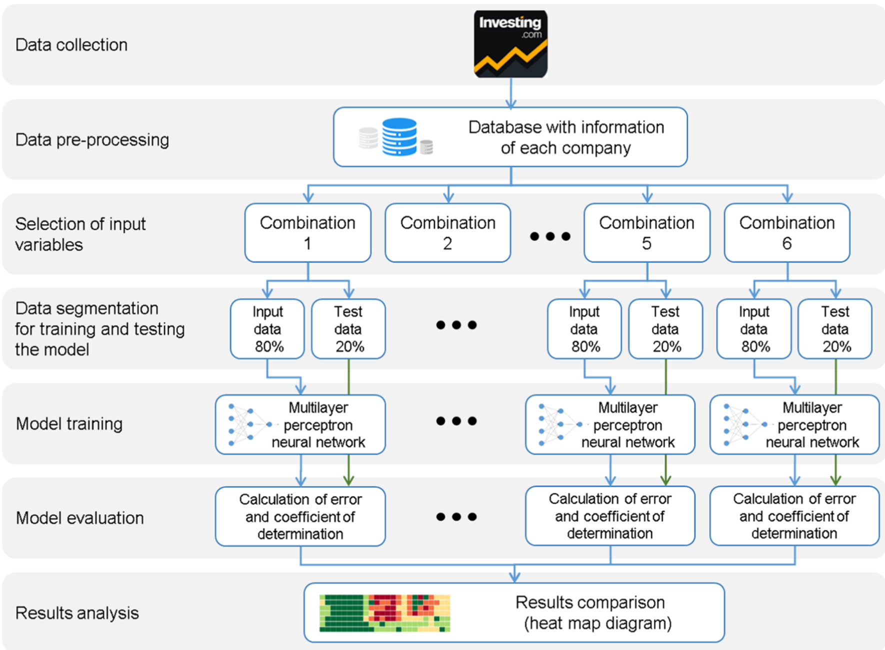

Fig. 5 Phase-by-phase flowchart of the process for building the machine learning model. *Source*: Prepared by author

established to compare and identify the combination that most effectively trains the model. Figure 4 details these combinations.

The combination including fundamental analysis and market sentiment is excluded because the exercise reveals that market sentiment does not significantly alter the outcome of the model incorporating only fundamental analysis variables.

Figure 5 depicts the phase-by-phase flowchart of the process, explained in the previous paragraphs, for building the machine learning model. Thos diagram illustrates that for each company, a multilayer perceptron artificial neural network is configured based on the defined combination types. Each network is evaluated independently, and their ultimate results are compared.

4.3 Model Validation

To assess the quality of the machine learning model, the coefficient of determination, the mean absolute error and the relative absolute error are calculated.

The coefficient of determination reflects the model's accuracy and tt ranges from zero to one:

$$\boldsymbol{R}^2 = \frac{\sum_{t=1}^{T}(\hat{\boldsymbol{Y}}_t - \overline{\boldsymbol{Y}})^2}{\sum_{t=1}^{T}(\boldsymbol{Y}_t - \overline{\boldsymbol{Y}})^2} \tag{2}$$

where:

$\hat{\boldsymbol{Y}}_t$ the estimation of a model according to what the explanatory variables are worth;

$\overline{\boldsymbol{Y}}$ is the mean of the variable Y.

According to Hernández et al. (2018) and considering the sample size, the neural network model for this case study is representative if it exhibits a determination coefficient greater than 80%.

On the other hand, the mean absolute error (MAE) indicates the size of the forecast error. The formula for calculating MAE is:

$$MAE = \frac{\sum \left| Y_t - \hat{Y}_t \right|}{n} = \frac{\sum \left| e_t \right|}{n} \tag{3}$$

where:

$\boldsymbol{e}_t$ is the forecast error in period t;

$\boldsymbol{Y}_t$ is the real value of the variable in period t;

$\hat{\boldsymbol{Y}}_t$ is the predicted value of the variable in period t.

For this research, which uses thirty-three representative companies belonging to the S&P 500 with an average stock price of $231 USD, the neural network model's accuracy is considered acceptable when the MAE is less than 5% of the average stock price, that is, less than 11.55.

Finally, the relative absolute error (RAE) is also calculated. According to Cichosz (2014), RAE is mainly used to evaluate the performance of a predictive model:

$$\boldsymbol{RAE} = \frac{\sum_{t=1}^{T} \left| Y_t - \hat{Y}_t \right|}{\sum_{t=1}^{T} \left| Y_t - \overline{Y} \right|} \tag{4}$$

where:

$\boldsymbol{Y}_t$ is the real value of the variable in period t.

$\hat{\boldsymbol{Y}}_t$ is the predicted value of the variable in period t.

$\overline{\mathbf{Y}}$ is the mean of the variable Y.

The RAE is expressed as a ratio that compares the mean error of the model with the errors produced by a generic model. An effective forecasting model produces a ratio close to zero. For this research, the neural network model is considered reliable when the RAE is less than one.

5 Results and Discussion

Tables 7 and 8 present the sector MAE and RAE as heatmaps, where the lowest value is marked in green and values exceeding the defined range are marked in red.

As observed, the model achieves varying performances depending on the combination type and sector. For example, for the communication services sector, combination four (incorporating variables from fundamental and technical analysis) exhibits the highest MAE and RAE values, while for technology, the model performs better with combination four, achieving some of the lowest MAE and RAE values in the table.

However, despite the differences by sector and combination, the trained machine learning model can be concluded to have an adequate degree of reliability for predicting the future performance of a company's stock in any sector of the S&P 500, as the metric values do not exceed the defined ranges on any combination or sector.

As a second analysis, Table 9 presents the coefficients of determination through a heatmap where the highest value is represented in green and the lowest value in red. The closer the value is to 100%, the more accurate the model is.

Table 7 Heatmap diagram of the average mean absolute error per sector. *Source*: Prepared by author

Lower accuracy → Higher accuracy*

Sector	Combination 1: Fundamental analysis	Combination 2: Technical analysis	Combination 3: Market sentiment	Combination 4: Fundamental analysis + Technical analysis	Combination 5: Technical analysis + Market sentiment	Combination 6: Fundamental analysis + Technical analysis + Market sentiment
Technology	1.709	1.215 *	1.341	1.582	1.255	1.637
Health care	2.079	1.715 *	1.911	2.200	1.977	1.971
Consumer discretionary	1.418	1.302 *	1.320	1.604	1.574	1.348
Financials	0.415 *	0.421	0.494	0.641	0.511	0.517
Communication services	4.782	0.997	1.037	7.656	0.773 *	7.587
Industrials	3.645	1.948 *	2.110	4.102	2.090	4.142
Consumer staples	1.012	0.726	0.561	1.107	0.555 *	0.924
Materials	1.271	1.514	3.048	2.806	1.207 *	2.163
Energy	2.207	1.649 *	3.979	2.405	3.181	3.204
Utilities	0.941 *	1.923	2.550	1.299	3.001	3.190
Real estate	1.587 *	1.897	3.216	2.204	2.222	3.084

Table 8 Heatmap diagram of the average relative absolute error per sector. *Source*: Prepared by author

Lower accuracy → **Higher accuracy** *

Sector	Combination					
	1 Fundamental analysis	2 Technical analysis	3 Market sentiment	4 Fundamental analysis + Technical analysis	5 Technical analysis + Market sentiment	6 Fundamental analysis + Technical analysis + Market sentiment
Technology	0.357	0.183	0.349	0.166	0.290	0.116 *
Health care	0.396	0.359	0.307	0.122 *	0.224	0.226
Consumer discretionary	0.221	0.263	0.142 *	0.280	0.332	0.232
Financials	0.171 *	0.312	0.341	0.378	0.283	0.271
Communication services	0.855	0.210 *	0.444	0.981	0.360	0.897
Industrials	0.385	0.206 *	0.335	0.501	0.294	0.516
Consumer staples	0.433	0.235 *	0.298	0.483	0.339	0.274
Materials	0.183 *	0.315	0.260	0.399	0.258	0.324
Energy	0.262	0.292	0.319	0.318	0.246 *	0.303
Utilities	0.391	0.217 *	0.395	0.498	0.245	0.443
Real estate	0.162	0.139 *	0.353	0.232	0.372	0.252

First, for all stocks, there is at least one combination with a coefficient of determination greater than 80%, which indicates that the selection and parameterization of the machine learning model is appropriate.

Aligning with the previous observation, interestingly, if we analyze by sector as shown in Fig. 6, the coefficient of determination exceeds 80% regardless of the combination in some sectors, including Technology, Health care, and Consumer discretionary. However, there are also sectors where more than half of the possible combinations do not yield the minimum acceptable coefficient of determination, such as Communication services, Utilities, and Industrials.

The graph shows, depending on the type of company or sector being analyzed, selecting the appropriate type of machine learning model is crucial. If the model is not suitable for the sector from the outset, it will not have the necessary quality to effectively predict the future performance of a stock regardless of the amount and type of data used for training.

Furthermore, the analysis shows that a direct relationship exists between the type of company and/or sector and the most appropriate combination of variables for the model. For example, for the present case study, calculating the average coefficient of determination by sector, as in Table 10, reveals that all three companies the Technology sector exhibit the highest coefficient of determination with combination number three, which incorporates market sentiment as a variable for training the model. Conversely, combination number three results in the lowest coefficient of determination for the companies in the Utilities sector. The analysis indicates that using combination two, which incorporates variables from technical analysis, is preferred for these companies.

Table 9 Heatmap diagram of the coefficient of determination by company. *Source*: Prepared by author

Lower accuracy → Higher accuracy *

Sector	Combination 1: Fundamental analysis	2: Technical analysis	3: Market sentiment	4: Fundamental analysis + Technical analysis	5: Technical analysis + Market sentiment	6: Fundamental analysis + Technical analysis + Market sentiment
Technology	88.899%	91.086%	91.122% *	90.227%	91.080%	90.010%
	86.005%	87.871%	88.038% *	86.567%	87.805%	87.323%
	86.136%	87.274%	87.992%	86.740%	88.010% *	87.387%
Health care	87.107%	88.194%	88.374% *	86.824%	88.171%	86.813%
	89.754%	89.803%	89.852% *	88.813%	89.827%	88.828%
	85.287%	87.012%	86.623%	86.489%	87.257%	87.542% *
Consumer discretionary	86.323%	86.846%	87.072%	87.054%	86.667%	87.145% *
	90.443%	90.502%	90.562% *	90.356%	90.503%	90.358%
	85.821%	85.905%	86.580%	85.910%	86.962% *	86.654%
Financials	88.748%	88.737%	88.886% *	88.754%	88.737%	88.757%
	90.534% *	90.467%	90.441%	90.532%	90.435%	90.519%
	85.361%	83.265%	83.624%	86.639% *	84.245%	85.298%
Communication services	24.685%	86.667%	87.183% *	37.269%	86.694%	50.208%
	42.902%	82.793%	82.958% *	55.620%	82.773%	64.691%
	55.672%	62.038%	84.068% *	51.752%	83.684%	60.108%
Industrials	52.207%	81.514%	81.891% *	39.631%	81.537%	74.498%
	86.911%	88.007%	87.638%	86.774%	88.272% *	86.485%
	74.023%	76.519%	80.236% *	77.774%	79.529%	77.485%
Consumer staples	89.174%	89.468%	88.454%	89.046%	89.490% *	89.044%
	72.296%	87.921% *	86.136%	68.778%	87.897%	69.784%
	83.020%	84.051%	84.918%	84.349%	85.114%	86.507% *
Materials	85.134%	81.184%	85.360% *	68.391%	80.335%	67.252%
	90.633%	90.658% *	89.548%	90.627%	89.654%	90.604%
	84.935%	85.320%	82.207%	86.360% *	82.932%	86.005%
Energy	89.242%	89.204%	89.166%	89.256% *	89.187%	89.208%
	86.995%	87.009%	83.103%	86.929%	87.053% *	86.929%
	84.691%	85.608%	84.305%	86.625% *	84.967%	84.354%
Utilities	69.661%	80.584% *	68.682%	77.214%	64.209%	80.264%
	83.399%	85.820%	76.108%	86.408% *	80.729%	81.177%
	79.203%	78.368%	62.694%	77.393%	67.360%	80.302% *
Real estate	89.993%	89.368%	86.361%	90.598% *	88.361%	89.857%
	87.281%	85.852%	82.691%	88.019% *	84.369%	87.361%
	84.938%	82.761%	81.992%	85.215%	83.438%	86.618% *

Relating the above, in Fig. 7 for each sector the type of combination with the highest coefficient of determination was identified, for example Health care and Consumer staples exhibit the highest coefficient of determination value with the combination five. Additionally, the average number of opinions by sector was added.

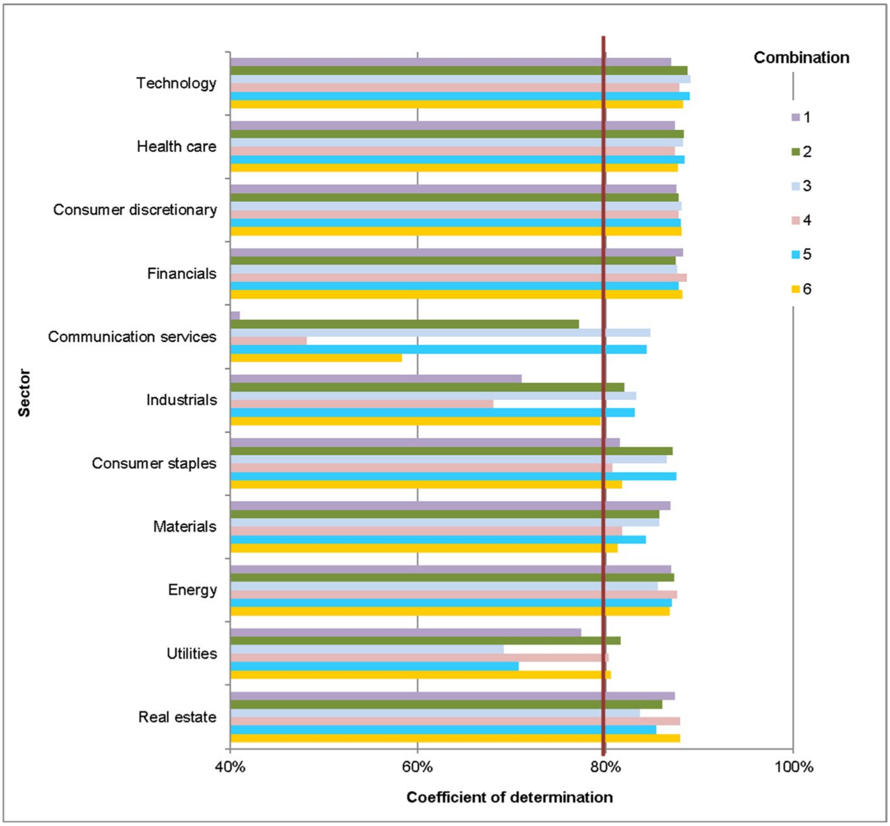

Fig. 6 Graph of coefficient of determination by sector and combination type. *Source*: Prepared by author

This reveals a direct relationship between the number of opinions and the combination with a higher determination coefficient. For example, sectors with a higher average of opinions, such as the Technology, Industry and Communications Services sectors, exhibit the highest coefficient of determination value with the combination that incorporates market sentiment (combination three).

In contrast, for sectors with lower monthly average opinion numbers, such as Materials or Utilities, the highest coefficient of determination is obtained with variables for fundamental analysis and technical analysis (combination one and two respectively).

Table 11 presents the coefficient of determination for the S&P 500, derived from the coefficients of determination for the eleven sectors comprising the index. While the simple average is provided, it should be noted that the sectors vary in the number of companies they include, as illustrated in Fig. 1. Therefore, a weighted average, considering the distribution percentages, was also calculated.

The result generated by the simple average reveals the combination of variables with the highest reliability percentage for training the model is the technical

Table 10 Heatmap diagram of the coefficient of determination by sector. *Source*: Prepared by author

Lower accuracy (Lower coefficient of determination) → **Higher accuracy*** (Higher coefficient of determination)

Sector	Combination 1: Fundamental analysis	Combination 2: Technical analysis	Combination 3: Market sentiment	Combination 4: Fundamental analysis + Technical analysis	Combination 5: Technical analysis + Market sentiment	Combination 6: Fundamental analysis + Technical analysis + Market sentiment
Technology	87.013%	88.744%	89.051%*	87.845%	88.965%	88.240%
Health care	87.383%	88.336%	88.283%	87.375%	88.418% *	87.728%
Consumer discretionary	87.529%	87.751%	88.071%*	87.773%	88.044%	88.052%
Financials	88.214%	87.490%	87.650%	88.642% *	87.806%	88.191%
Communication services	41.086%	77.166%	84.736%*	48.214%	84.384%	58.336%
Industrials	71.047%	82.013%	83.255%*	68.059%	83.113%	79.489%
Consumer staples	81.497%	87.147%	86.503%	80.724%	87.500% *	81.779%
Materials	86.901%*	85.721%	85.705%	81.793%	84.307%	81.287%
Energy	86.976%	87.273%	85.525%	87.603% *	87.069%	86.830%
Utilities	77.421%	81.591%*	69.161%	80.338%	70.766%	80.581%
Real estate	87.404%	85.994%	83.681%	87.944%	85.389%	87.945% *

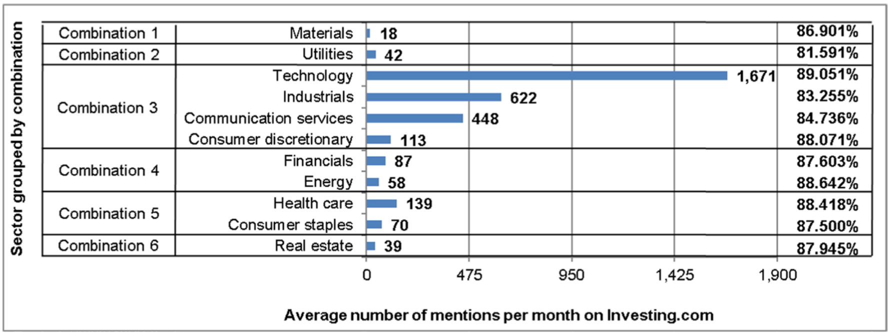

Fig. 7 Grouping of sectors with the type of combination that presents the highest coefficient of determination. *Source*: Prepared by author

analysis (combination three), with a value of 85.384%. Combination number five (Technical analysis plus market sentiment) is the second most reliable, and the market sentiment is third with a value of 84.693%.

However, considering the coefficient of determination weighted average by sector, reveals that the accuracy percentage increases for all combinations, for example, combinations that include market sentiment (combination three, five and six) have the highest average increase of 1.5%. This confirms the results of Alsing and Bahceci (2015) and Ordóñez (2017) who affirm the market sentiment can be used as a complement that adds precision to an existing model.

Table 11 Heatmap of the simple and weighted average by sector of the coefficient of determination of the S&P 500. *Source*: Prepared by author

Lower accuracy (Lower coefficient of determination) → Higher accuracy* (Higher coefficient of determination)

Average	Combination 1: Fundamental analysis	2: Technical analysis	3: Market sentiment	4: Fundamental analysis + Technical analysis	5: Technical analysis + Market sentiment	6: Fundamental analysis + Technical analysis + Market sentiment
Simple average	80.225%	85.384%*	84.693%	80.574%	85.069%	82.587%
Weighted average by sector	80.244%	86.156%	86.779%	81.005%	86.884%*	83.303%

With this, the order of the combinations with the highest reliability percentage is also adjusted, with combination number five (Technical analysis plus market sentiment) now in first place, with a value of 86.884%, followed by market sentiment with a value of 86.779% in second place, and technical analysis with a value of 86.156% in third place.

This confirms the hypothesis that creating a machine learning model that involves variables of stock analysis and qualitative data such as market sentiment can yield forecasts that are presumably closer to the future performances of stocks. However, unlike previous research, this research contributes to identifying the sectors where it is appropriate to use market sentiment and where it is not.

In this sense, Fig. 8 shows the proportion of each sector compared to the total number of companies that compose the S&P 500. For 80% of them, the combinations that incorporate market sentiment as a variable to train the model, present the highest determination coefficient value; but for Financials, Materials, Energy and Utilities sectors, which are sectors with a low number of opinions, the machine learning model is more effective using other types of analysis such as fundamental analysis and technical analysis.

This confirms the findings of Didenko et al. (2023), Hassan (2024), Sandhu (2005), who affirm the limited number of opinions in social networks regarding sectors such as finance or energy can be attributed to various factors. These include the complexity of these sectors, which require a certain level of experience and knowledge to understand; the regulatory environment, as these industries are heavily regulated, leading organizations to be cautious in sharing information; and the accessibility of data, as these sectors have less data accessibility compared to consumer-centric industries where data is readily available. As a result, only a small group of individuals who are knowledgeable about and interested in these sectors share their opinions in social networks.

A point to highlight is that financial markets typically exhibit anomalies and operate under uncertainty. During the study period of this research, moments of volatility were observed due to the COVID-19 pandemic. While these variations can indeed affect model results, the high coefficient of determination found in this

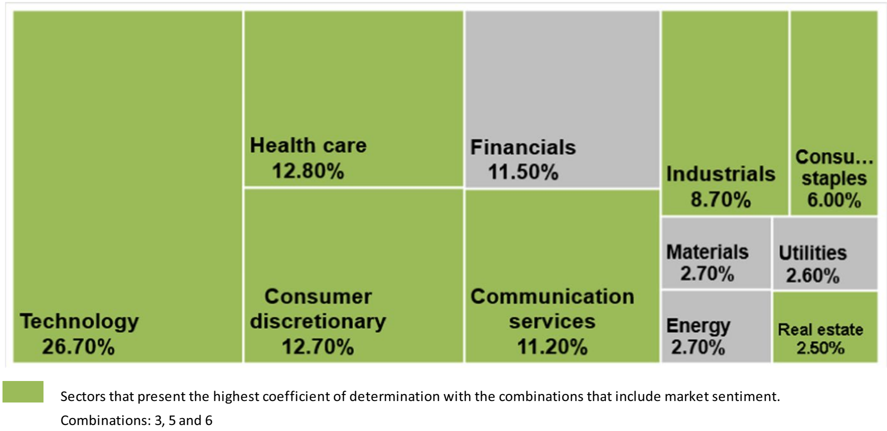

Fig. 8 Sectors with the highest coefficient of determination with combinations that include market sentiment. *Source*: Prepared by author

research supports the conclusions of Oyewole et al. (2024) and Lee et al. (2024). They assert that neural networks, when used in conjunction with market sentiment, can capture complex market patterns and dynamically adapt to volatility. This is because market sentiment measures the public's reaction to market volatility, and neural network models have a superior ability to adapt quickly to such volatility compared to other models.

Finally, Table 12 presents a comparison between the proposed models that incorporate market sentiment as a variable (combinations three, five, and six, highlighted in blue) and the research described in the related work section.

Considerations:

- The accuracy results of this research are those calculated in Table 11 (weighted average by sector).
- For the comparison, models were grouped based on the type of variables used for training each model.
- There are studies that cannot be compared due to different evaluation methodologies, marked with an asterisk (*). However, they are included in the comparative table since they used similar models and variables.

As a first point to highlight, this analysis confirms the statements made by Mittal et al. (2019), Kour (2024), Goodfellow (2016) and Fuentes (2020) who affirm that the accuracy depends not only on the model, but also on the problem to be solved and the quantity, quality and types of data selected for training. Although there are studies that use the same model, the difference in accuracy depends on the different scopes and the information used.

Among the group of research that use market sentiment as a variable, it is observed that the proposed model achieves a higher accuracy of 86.78%, followed by research #4 by Sarmiento (2017), which utilizes a Support Vector Machine

Table 12 Comparison of the model's accuracy versus previous research results. *Source*: Prepared by author

Variables	#	Meachin learing model used	Accuracy	Authors	Years
Market sentiment	-	*Multilayer perceptron artificial neural network*	*86.78%*	*Arauco and Martínez*	*2024*
	1	Emotion enhanced convolutional neural network + Denoising autoencoder + Long short-term memory model	MAPE *1.1%	Zhao and Yang	2023
	2	Naive Bayes and Logistic regression classifier	60% to 80%	Javed Awan et al	2021
	3	Logistic regression and TF-IDF	58% to 65%	Gupta and Chen	2020
	4	Support Vector Machine	86%	Sarmiento	2017
	5	CashTagNN + Feed-forward Neural Network	85%	Rajesh	2016
	6	Multilayer perceptron artificial neural network	52.44%	Peng and Jiang	2016
	7	Feed-forward neural network	65%	Alsing and Bahceci	2015
Technical analysis + Market sentiment	-	*Multilayer perceptron artificial neural network*	*86.89%*	*Arauco and Martínez*	*2024*
	8	Bidirectional Encoder Representations from Transformers + Gated recurrent unit	57%	Hung et al	2024
	9	Bidirectional Encoder Representations from Transformers + Recurrent neural networks	MAPE *3.05%	Lee et al	2024
	10	Random Forest	68.40%	Gálvez	2016
Fundamental analysis + Technical analysis + Market sentiment	-	*Multilayer perceptron artificial neural network*	*83.30%*	*Arauco and Martínez*	*2024*
Fundamental analysis	11	Feed-forward Neural Network + Random Forest + Adaptive Neural Fuzzy Inference System	Portfolio Score * 0.759 "Buy"-0.335 "Sell"	Huang et al	2021
Technical analysis	12	Multilayer perceptron artificial neural network	64%	Ordóñez	2017

model resulting in an 86% accuracy. On the other hand, despite research #6 by Peng and Jiang (2016) using the same model as this research, the difference in accuracy is mainly due to their calculation of market sentiment using financial news. This confirms that the selection of the information source that will train the model is directly related to the final accuracy of the model.

Among the group of research that use market sentiment and technical analysis as variables, it is observed that the proposed model also has the highest accuracy, 86.89%, followed by model of Gálvez (2016) with 68.40% accuracy. In this comparison, both models are based on information from social networks and technical indicators; however, Gálvez (2016) uses a random forest model, confirming that with this combination of variables, an artificial neural network multilayer perceptron model is more efficient.

Finally, it is observed that the other studies do not use market sentiment, technical analysis, and fundamental analysis as variables in the same model. Although out of the 6 combinations presented in this research, this combination did not achieve the highest accuracy, 83.30%, it does outperform some other models presented in the related work, which presents an area of opportunity and a contribution of this research.

6 Conclusions and Future Work

Within the financial environment, globalization and great technological advances have currently allowed the stock market to be brought closer to investors through online platforms for buying and selling investment instruments, providing access to a large amount of real-time information.

Therefore, if stock market decision makers wish to achieve good performance when buying or selling investment instruments, these instruments must be incorporated into current strategy models that process large amounts of information and consider other variables, such as market sentiment.

To address this, this work was conducted to demonstrate obtaining a forecast that presumably better aligns with the future performance of a stock is possible if a machine learning model involving variables of stock market analysis and qualitative data such as market sentiment is created in a multilayer perceptron artificial neural network programmed in the web solution Azure Machine Learning Studio. This research makes the following four contributions:

- It identifies the best variables combinations to train a neural network model depending on the market sector to be analyzed.
- It demonstrates that, by using market sentiment, it is possible obtain a high accuracy or increase the accuracy to an existing model.
- It evolves the way of thinking and supports eliminating the paradigm that one type of analysis is exclusive of the other; in contrast, it confirms that their combination yields a stronger investment strategy.

- It demonstrates that new technologies, such as artificial intelligence, will be key for precisely and quickly analyzing a significant amount of information available on the web in the future, reducing the reaction times needed for decision making.
- It promotes strategic thinking for decision makers in the stock market, allowing them to reduce emotional bias in decision making through the use of current investment strategies.

In summary, this research was conducted to address a real financial problem through strategic thinking, thus reducing emotional bias for decision makers in the stock market through the analysis of qualitative and quantitative data. This research provides a model that allows for a greater understanding of the behavior of stocks and the relationship between them and leaves the research path open for applying artificial intelligence models in the financial field.

The results of the case study indicate that, depending on the type of company or sector to be analyzed, selecting the type of machine learning model plays a crucial role in the model, with a direct relationship existing between the type of company and/or sector and the most appropriate combination of variables to feed the model.

Additionally, the results also showed that the model's accuracy percentage for the S&P 500 is higher in the combinations that include market sentiment than in the combinations that do not include it, thus confirming the hypothesis of this research.

For these reasons, it is concluded that incorporating market sentiment as an additional variable in the model yields forecasts that better align with the future performance of a stock. However, a considerable amount of data is essential for its calculation, as the results also exhibited a direct relationship between the number of opinions and the model's accuracy when using the combinations that incorporated market sentiment.

The principal challenge to produce a reliable model was to put together a sizable dataset for experimenting. The original data set consisted of a large number of unstandardized values in different formats and sources, so we had to go through a series of data preprocessing steps to prepare them for training and testing the model. In the end, more than 1,489,000 data were processed in total (approximately 45,140 data for each company).

One of the main limitations of this research is that the analysis considers only thirty-three of the five hundred companies that compose the S&P 500 due to the need for more robust software and infrastructure to process the data of all companies in this index. To mitigate this issue and maintain a balanced proportion among the sectors that compose the index, this case study was limited to three representative companies per sector, considering criteria such as trading volume, historical performance, and investment experience with the selected issuers.

For subsequent studies, it is proposed to train the model using other companies belonging to the S&P 500 to confirm whether similar results can be obtained by considering other selection criteria and to even conduct a case study considering other indexes, sectors or companies that are not within the scope of this paper.

Additionally, it is proposed to add a profit measure in an investment simulation to confirm the model's reliability by creating an automatic process to extract, transform and load the data into robust software to calculate the results daily.

Another limitation of this research is that only one source of free information (Investing.com) was considered to calculate the market sentiment, so another interesting proposal is to consider other sources of information, such as opinions or comments from different social networks and even information generated in different formats, for example, reactions, text, or videos.

Finally, following this line of research, other possible future lines of work are using a different time frame, for example, real-time analysis; using another artificial intelligence model; and applying the case study with companies from other markets to validate a direct relationship exists between the region and the model accuracy by incorporating market sentiment as a variable.

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Data Availability Sample data of stock market evaluations and market sentiment supporting machine learning model are publicly available in the OSF repository, as part of this record, DOI: https://osf.io/s8ah9/?view_only=c709f77306aa43d2a401a2246c592686 (Arauco Ballesteros, 2023).

Declarations

Conflict of interest All authors certify that they have no affiliations with or involvement in any organization or entity with any financial interest or non-financial interest in the subject matter discussed in this manuscript.

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