CNN-based Investment Strategy Using Technical Indicators

by

Saken Mukanov

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Author . . . .
Department of Computer Science
14 April 2024

Certified by . . . .
Supervisor
Professor M. Fatih Demirci
Thesis Supervisor

Certified by . . . .
Internal examiner
Professor Meiram Murzabulatov
Thesis Supervisor

Certified by . . . .
External examiner
Professor Anara Sandygulova
Thesis Supervisor

Accepted by . . . .
Chairman
Dean, School of Engineering and Digital Sciences Yelyzaveta Arkhangelsky

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Abstract

Since the dawn of time, both individuals and institutions have been in pursuit of strategies to amplify their wealth, recently, more in the financial world. This process of increasing one's wealth changed and evolved in the same manner as did technological progress, particularly with the integration of artificial intelligence (AI) and machine learning (ML) technologies in the financial analysis. Among these advancements and innovations, Convolutional Neural Networks (CNNs) have emerged as a formidable tool for forecasting market trends and predicting outcomes of transactions. Current investment strategies mostly use numerical data, technical indicators derived from numerical data, and the intricate algorithms of neural networks (NNs). However, the current methodologies for data transformation misses the necessary diversity to fully exploit the capabilities of advanced neural network models.

This paper aims to bridge this gap by proposing a novel approach that utilizes models with technical indicators with new data format. The end goal of this paper is to develop a robust investment strategy that utilizes power of NNs while using uncommon data transformation in order to achieve great results in accuracy and reliability of trend prediction. To achieve this goal, this paper introduces a methodological know-how that methods that involve converting technical indicators into images and feeding them to NNs, specifically NNs that are well adept in image classifications. Particularly, leveraging CNN's excellence in detecting unseen patterns within these visual representations, offering a enhancing the effectiveness of investment strategies through the power of image-based data analysis.

Thesis Supervisor: Supervisor
Title: Professor M. Fatih Demirci

Thesis Supervisor: Internal examiner
Title: Professor Meiram Murzabulatov

Thesis Supervisor: External examiner
Title: Professor Anara Sandygulova

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Chapter 1

Introduction

1.1 Motivation

Financial market - a complex set of data, trends and indicators, has been a meeting place for investors who are trying to maximize their profits and returns and business owners trying to expand their businesses. Traditionally, investment strategies have largely been associated with fundamental and technical analysis with a heavy reliance on numerical data points and historical market behavior. Though, as markets evolve, the volume, velocity, and variety of financial data expand significantly, that presents new opportunities for investors to use underutilized tools and therefore increase their returns on investments (ROI).

Motivation for this research stems from a critical observation - although the variety of the data has been increasing, primary tools used for the analysis have remained somewhat similar. While traditional investment strategies such as statistical analysis can still be utilized to gain profits, they do not use full variety of available data. Particularly recognizing and interpreting complex patterns might be difficult to see inside numbers alone. This underutilizaiton has real-world applications for the efficiency of investment decisions. With the recent rise of machine learning technologies, particularly Convolutional Neural Networks (CNNs), a new horizon has opened up. These technologies have been changing the way financial analysis is done by allowing the extraction and undesrtanding of intricate patterns from vast datasets, patterns that may elude human analysts or traditional computational methods.

CNNs are renowned for visual image recognition and classification, and could be introduced as a potential tool in extracting previously unseen features and patterns from data. Transforming financial data into visual formats and feeding it to CNN can be helpful in identifying complex patterns from images, offering a fresh perspective on market analysis that goes beyond the capabilities of statistical analysis, and utilization of technical indicators by data analysis. This approach does not apply new tools or architectures to the existing data, but it alters the input data by transforming it to unutilized data format to access CNN's ability in image classification.

The motivation for this study is further increased by potential to enhance predictive capabilities of the models to gain more potential gains from investment decisions, as it will add more attractiveness to the system that outperforms traditional statistical analysis and current machine learning solutions. By integrating CNNs into the investment strategy framework, it is possible to achieve the goal of monetary advancements.

In summary, the motivation behind this research has multiple sides: addressing limitations of traditional investment strategies, harnessing the potential of CNNs in financial analysis, enhancing predictive accuracy of investment decisions.

1.2 Current data format

In recent years, investment strategies have significantly evolved with the addition of machine learning technologies and the principles of data science, altering the way financial analysis is done. This evolution has been particularly pronounced with the rise of CNNs, which are highly efficient and powerful tools in machine learning. CNNs are renowned for their proficiency in analyzing images and recognizing complex patterns, and are now being used to predict market trends. Their ability to process and interpret huge amounts of data makes them at the forefront of technological advancements in finance.

Currently, there is a heavy reliance on use of technical indicators and numerical values, along with the complexity of neural network models, however a key limitation in these approaches is the lack of diversity in data transformation. This limitation is particularly significant when considering the potential of certain neural networks, such as CNNs, which can perform on a varied dataset to fully use their capabilities in pattern recognition and predictive analysis. The existing strategies often fail to convert the available data into formats that these sophisticated neural networks can effectively utilize. This gap between the data's current form and the preferred input for these neural networks, results in the possible underutilization of the models. Therefore, there's a need to alter the pipeline of these strategies to include more diverse data transformation techniques, to enable more complex usage of the neural networks' potential.

Main objective of this research is to build an automated investment strategy that uses the capabilities of CNNs with technical indicators employed in financial markets. To achieve this, the proposed methodology takes a novel approach: it involves converting technical indicators, which are mostly numerical data, into images. This transformation is crucial as it utilizes CNNs' strength of extracting complex patterns from images. By translating these technical indicators into images, the study leverages the deep learning prowess of CNNs to analyze and predict market momentum.

Frameworks used to analyze data from DOW-30 stocks spanning the period from 2007 to 2016.

- Build a pipeline to extract raw data of DOW-30 stocks
- Derive technical indicators from raw data
- Transform technical indicators into images
- Develop and validate CNN-based financial forecasting models
- Compare the performance of these models against traditional forecasting methods
- Assess the models' effectiveness in real-world financial scenarios

In this paper, this section is followed by a thorough reviewing related works, delving into existing academic works and methodologies within the financial world and how current technologies have changed the way financial analysis is done. Related works will serve as foundation for a comprehensive evaluation of the proposed approach. Subsequently, the methodology of this research is expanded on, looking into the data sources, analytical techniques and machine learning models. Finally, the paper shows main findings and results, reflects on potential impact to the broader field of financial investment strategies.

Chapter 2

Related work

Stock market has come quite a journey from its appearance, its evolution was always dependent on the data availability, speed of transmission, and integrity. This dependence has transformed the stock market from a basic system of trading into a complex and integral part of the global economy.

The stock market is traced back to the late 16th century when the Amsterdam Stock Exchange was established [1]. This was a time when companies started needing more and more capital, leading to a single individual or even family's wealth being not enough to provide for, leading to the birth of sharing the ownership of the company. Investors could buy or sell shares in a company, therefore owning a piece of the business, and share in its profits or losses. This mechanism enabled companies to access the needed capital for expansion while distributing the investment risk.

As time passes, the stock market cannot remain unaltered due to its nature of dependence on the data availability, velocity, variety. Technological advancements of 20th and 21st century change the way data is accessed, the time it takes for any news to be transferred to individuals and institutions, and new mathematical interpretations of company's success. This changes along with trading becoming more accessible to the general public by diminishing the need of broker made increasing and incredible involvement possible. This period also saw the introduction of complex financial instruments and the globalization of financial markets[5], [6].

Quite recently, with more and more advancements in Artificial Intelligence (AI) and Machine Learning (ML), and abundance of previously unseen amount of variety of data, it became possible to use these techniques to help investors and traders analyze the financial market trends deeper. These new technologies allowed professionals and amateurs to analyze vast amounts of data, predict market trends, and make investment decisions, signaling a new era in financial analysis and investment strategy [7].

Due to their nature, ML algorithms are indispensable tools in the hands of professional traders. They can access whole history of the companies, analyze amounts of data impossible for humans to analyze in a matter of seconds, identify patterns, trends, correlations that are not apparent to human analysts. On top of that, unlike humans, these AI agents do not possess emotions that typically alter human analysts' decision making, but they analyze potential gains with associated risks. Not only ML algorithms are capable of learning and executing orders, but they are able to learn and adapt over time. Through techniques like supervised learning, ML models can be trained on historical data, adjusted and refined as they are exposed to new data, enhancing their predictive accuracy.

Within ML models, the one that is especially proficient in analyzing and extracting features from images is Convolutional Neural Network (CNN). Its ability to recognize complex patterns in images, classification accuracy, ability to capture intricacies of the data are the key characteristics that allow it to be able to be used in financial forecasting. [17]

Exploring machine learning uses in finance prediction now and not long ago, lots of ways and models are looked into. The search starts with [9], giving a wide look at forecast methods. It begins by analyzing feelings from short social media posts to understand what people think about certain stocks. Algorithms applied include usual ones like Support Vector Machines (SVMs) and Random Forest (RF). The criticism points out that to make better predictions, there is a need for complex designs in models, which shows a basic difficulty when predicting finances.

Next, the paper referenced as [10] looks into how using more complex models can help in automatically understanding features and learning stock trading through reinforcement learning. This type of learning is similar to a reward and penalty system where the model gets rewards for successful trades and penalties for unsuccessful ones. They focus on the Deep Q Network (DQN) a lot and say it works better and with more precision than other deep reinforcement learning models, like Double-DQN or Dueling-DQN. This kind of comparison highlights how machine learning models are advancing in trading.

Further, [11]'s emphasis is examined on Long Short-Term Memory (LSTM) models. LSTM models are also known as Recurrent Neural Networks (RNN) that have solved vanilla RNN's problem of vanishing gradient that disallows RNNs to link events that are seperated by few generations of data. Due to that LSTMs can learn and analyze more complex and long-range patterns and its predictive accuracy in stock market is very high. Their work, aligning with the latest trends in deep learning, achieves remarkable precision in forecasting market closing prices, illustrating the growing reliance on deep learning techniques for nuanced financial analysis.

Authors [12], [13], and [14] present various methods, including neural networks, LightGBM, and NARMAX models. They apply their own models and techniques in different situations. The study in [12] looks at how neural networks work in the China finance market and finds they can predict returns across different markets. Also, research papers [13] and [14] look into complex systems such as BiGRU neural networks and Light Gradient Boosting Machine (LightGBM) structures to see their effectiveness for forecasting stock prices. These authors present different models in many scenarios, demonstrating that these methods are useful in a wide range of situations.

These studies collectively showcase that a handful of ML models offer distinct financial capabilities in financial forecasting. Some are good in sentiment analysis of the users towards specific stock, some use less sophisticated ML models and achieve good results, while other use very deep and complex models to achieve even greater insights and results of forecasting. This journey through various ML methodologies not only highlights the technological advancements in financial forecasting but also underscores the critical need for ongoing research and development to refine these tools for future financial landscapes.

Chapter 3

Methodology

In this section the process of the financial forecasting is outlined in details. As illustrated in Fig. 1, there are a total 5 steps in the process. First, in the data acquisition, the raw data of the DOW-30 mutual fund is collected, cleaned, refined, and preprocessed to remove inconsistencies, anomalies, and absence of data. After the first step, the collected raw data is transformed to various technical indicators, as the raw data on itself is not versatile enough to be able to do forecasting. If the data is not supplemented with these technical indicators, any model is not capable enough to be able to help out with prediction.

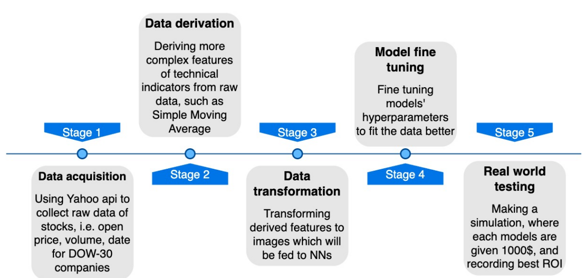

Figure 3-1: Pipeline of methodology

Next steps include transforming the supplemented dataset into visual form, feeding the dataset to various machine learning models, fine tuning them to get better accuracy on prediction outcomes. Final step is to take trained model, test it on the dataset that it had never seen, and calculate the return on the investment from pseudotrading.

Current approach's data labeling is different from previous approach [23], which makes difference in monetary ROI. In the previous approach, the methodology used for categorizing stock market actions was based on the utilization of 15-day sliding window periods, where the day being a maximum of the window meant being a "sell" day, being a minimum of the window meant being a "buy" day, and the rest being "hold" days. While this strategy may be beneficial for increasing one's wealth, there are limitations associated with this approach.

Refined approach incorporates a methodology of labeling in the following format: a day is designated as profitable if the stock's price increases by at least 4% within a subsequent 10-day period. Conversely, a day is classified as not profitable if a decline of 10% or more is observed in the stock price over the same future interval, and neutral days otherwise. This methodological shift has materially enhanced the performance of our predictive models.

The current approach has surpassed the limitations of the previous approach in data imbalance. "Hold" days used to take vast majority of the dataset, while currently dataset is more balanced.

3.1 Data Acquisition

As the initial step, data acquisition is mostly about querying data from public sources to the local machine. At this point Yahoo Finance library was chosen as it contains all the necessary raw data for DOW-30 stocks. The platform provides needed data for the whole period of training and testing, with the granularity of days, and free of charge. The data's granularity and detailed historical records allow nuanced back-testing, ensuring that models are not just theoretically sound but also practically viable.

3.2 Data cleaning and transformation

After raw data is collected, next step involves data cleaning, transformation, normalizing. it is important to note that prices have to be adjusted prices, factors such as stock dilution may distort the prices. After the data is cleaned and transformed, the next step is to derive all the necessary technical indicators from the transformed data. These indicators are fundamental tools that help financial professionals in their analysis, therefore are most likely useful for the models' analysis. Technical indicators may provide very useful insights of the current market trends, momentum, volatility, and market sentiment.

Technical indicators such as Simple Moving Average (SMA) and the Relative Strength Index (RSI) are one of the most important tools in professional traders' arsenal. SMA helps identify the direction of the trend, smoothing out price noise to create a single flowing line, which makes it easier to identify the direction of the trend. There are few variations of the indicator, such as Exponential moving average, triple moving average. The RSI measures the speed and change of price movements which indicates whether the stock is overbought or oversold.

Such indicators provide objective measurements of the market, and generally help to quantify the ratio of being overbought or oversold. Not only they help to identify general momentum of the market, but also indicators like Moving Average Convergence Divergence (MACD), Bollinger Bands, and Fibonacci retracements offer deeper insights. MACD identifies trend changes, while Bollinger Bands provide insights into price volatility, and Fibonacci retracements help identify key support and resistance levels.

3.3 Technical indicators

The Relative Strength Index, also named RSI, is a momentum oscillator that estimates the speed and change of price movements. It fluctuates between zero to 100. According to Wilder's explanation, most people consider RSI overbought when it goes beyond 70 and oversold if it falls under 30. Traders often use the RSI as a way to find possible points of reversal. They do this because it can show when an asset is becoming too much in demand (overbought) or under demand (oversold). They look at these signs like a message saying that the asset's direction might switch soon.

WR: Williams Percent Range, is a momentum indicator that helps to identify when a financial instrument is in an overbought or oversold stage. Similar to RSI, it oscillates between 0 and -100. If the value drops below -80 this means it's becoming too much and needs selling off (overbought), but if it rises above -20 then there's not enough demand for buying so we say this as being oversold. This instrument is very useful for finding out the exact moment when price turning points might happen.

SMA: The Simple Moving Average technique gives a basic average of costs. It adds up the selected prices range, usually closing prices, and then divides this total by number of periods in that range. This is one of the most common moving averages as it creates a smooth line that can help to identify the trend's direction and possible levels for support or resistance.

EMA (Exponential Moving Average): Similar to the SMA, this method also takes into account an average of a certain number of recent prices. But, EMA puts more emphasis on the latest prices and reacts quicker to new data. Traders often use EMA for quickly catching trend direction, and sometimes along with SMA to find possible crossover spots.

VWMA (Volume Weighted Moving Average) is a type of moving average which considers more important price data with higher volume. It can give additional insight into the strength and potential turning points in trend because it includes volume information, unlike the normal moving averages.

TEMA: Triple Exponential Moving Average is a technique to tackle the lag issue in standard EMAs by tripling the weight of recent prices. This method proves beneficial for traders functioning within short-term periods and attempting to capitalize on small price shifts. It assists in the quicker recognition of how the trend is progressing and its power, in comparison to regular EMAs.

CCI: The Commodity Channel Index, is a versatile indicator that assists in spotting new trends or highlighting extreme situations. It's frequently applied for measuring the disparity amid a security's value and its statistical mean. When values are high, it shows prices are very abnormal against average prices; when they're low, this signifies extremely low costs.

BOLL: Bollinger Bands consist of a middle band, which is a simple moving average (SMA), and two outer bands that represent standard deviations away from this SMA. Their size alters according to market volatility - they grow wider when there is greater price movement and contract during more peaceful periods. Traders use Bollinger Bands for determining if something becomes excessively bought or sold; this might indicate breakouts or changes in volatility.

SMMA: The Smoothed Moving Average (SMMA) is similar to EMA, but it smoothens over a longer period of time. Because of this longer smoothing, SMMA reacts less quickly to recent price changes. Traders often use this method when they want to confirm long trends without being disturbed by short-term fluctuations.

MSTD (Moving Standard Deviation): It is a statistical calculation that shows the price volatility during certain timeframe. Moving Standard Deviation or MSTD, often used together with other indicators, helps in assessing the risk related to price fluctuations of one security.

MFI (Money Flow Index): Money Flow Index, also known as MFI, is an indicator for momentum that takes into account price and volume data. It is often used to understand if an asset has been excessively bought or sold. MFI adds the changes in prices with the traded volumes, offering a wider view than what only indicators based on price can give.

StochRSI: Stochastic Relative Strength Index is a type of oscillator that falls between 0 and 1. It originates from RSI, but applies the formula of Stochastic Oscillator to it. This combination renders StochRSI more sensitive to changes in its underlying RSI, often used for identifying overbought or oversold conditions with more precision than regular RSI.

CHOP: The Choppiness Index is an indicator that serves to verify if the market exhibits choppiness, which refers to choppy trading or non-choppy trading. When this value becomes big, it suggests there's consolidation happening; when the value gets low, it hints at a trend occurring. This helper is often used for decisions about shifting towards strategies more effective in markets of range-bound trading compared with methods following trends.

KAMA method is created by Perry Kaufman. It alters its response to price adjustments. The moving average approaches prices when there is a swing in price, and then it stabilizes as the prices are steady. It can be particularly beneficial for traders who require an adjustable filter.

3.4 Numerical data to visual images

The cornerstone of the proposed approach is to use data in visual format to leverage neural networks' abilities to find complex and composite patterns within the data. The transformation converts raw data, derived technical indicators into images so that deep neural networks, such as Convolutional Networks can utilize its prowess in visual perception as they are adept at recognizing patterns in spatial data.

By converting financial data into images, we take advantage of CNNs' capacity to extract and learn hierarchical feature representation. This is especially useful in financial environments, as patterns may indicate trends, reversals, or other market dynamics. The visual representation enables CNNs to identify these patterns more accurately than standard numerical analysis approaches.

Furthermore, CNNs automate feature extraction, which represents a considerable improvement over older methods that require manual feature identification. They are made up of several layers, including convolutional layers, pooling layers, and fully connected layers, all of which help the network learn from difficult data. In the financial realm, this means CNNs may detect minor market signals within visual data, providing predictions or insights that even experienced professionals may miss.

The use of CNNs to turn financial indicators into visual representations is more than just a technical exercise; it significantly improves the interpretability and accessibility of financial data analysis. It enables analysts to visualize market behaviors, compare patterns, and make previously impossible forecasts with unprecedented accuracy and speed. This methodological shift marks a substantial advancement in how we interpret and exploit financial data, providing a more dynamic, intuitive, and powerful approach to market analysis.

The method to change numbers into pictures is a process that requires steps. It starts by making numbers in their feature sets normalized so they all have same scale. The following step consists of mapping the data onto a grayscale. Here, bigger values display as lighter shades while smaller ones show up as darker hues. This aids in pattern recognition using CNNs. After scaling, the data is reshaped to fit the input requirements of CNNs. For this step we use Python Image Library PIL, it converts these numerical arrays into standard image formats that can be processed by CNNs. The change allows CNNs to use their strong ability in recognizing patterns for finding complex and subtle market signals. This greatly enhances the analysis of finance and accuracy in predictions.

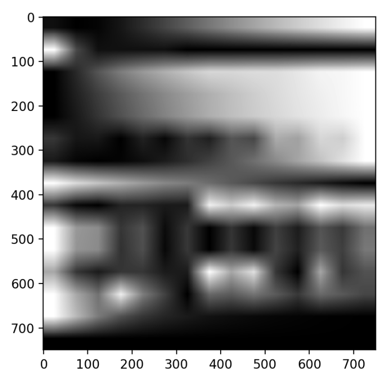

Figure 3-2: Image example of image visualized from numerical data

3.5 Predictive models

3.5.1 Supervised Machine learning

Supervised learning is a part of machine learning where the algorithm gets trained on dataset with labels. This means every sample in training set has correct output paired to it. The model learns how to map inputs and outputs by utilizing this information and then applies that mapping for making predictions on data not yet seen. Unsupervised learning is different because there are no labels given to the algorithm; instead it needs to discover structure within input data independently.

The data for training in supervised learning is a group of training examples. Each example has two parts: an input object (most of the time it is a vector) and wanted output value (also called supervisory signal). With help from the machine learning algorithm, we can study this set of training data to create an inferred function. It's possible to use that function later for mapping new examples. This process depends on the learning algorithm being able to make generalizations from known situations, as revealed by the training data, to unseen scenarios in a "reasonable" manner.

When selecting a machine learning method for financial forecasting, supervised learning is often chosen. This method involves training an algorithm on existing data, with inputs labeled according to the known outputs. The historical financial information that we possess is usually plentiful and contains precise timestamps. In such cases, it becomes feasible to generate labeled datasets where the inputs signify past financial indicators while outputs stand for future values or trends. For instance, a model could be trained using past stock prices along with different other financial indicators in order to forecast upcoming stock prices.

Additionally, in financial forecasting accuracy is very important because even a slight mistake can result in considerable losses. Supervised learning models can be thoroughly assessed and adjusted using past data, giving a level of trustworthiness to their ability for prediction. This is important for finance uses where those involved must rely on the model's forecasts when deciding what to do.

Financial markets are impacted by many different elements such as economic indicators, company earnings results and situations in geopolitics among others. Supervised learning models have the ability to combine all these varied data inputs for creating forecasts; they can learn intricate connections between various factors and financial results that might be challenging or even impossible for an analyst to understand.

This method helps with interpreting results as well: since we know how the ML models learn patterns in input-output mappings from training set, financial analysts can better understand why an algorithm made certain prediction by looking at specific features present within input vector which were used during training process itself. They could also identify if there were missing features or any other issues with the initial dataset setup. In short, supervised learning's capability to comprehend relationships between input and output through past experiences aligns well with main requirement of good quality feedback loop needed in finance forecasting tasks . Through this way we can more effectively use historical data analysis along with pattern recognition abilities provided by ML systems - not only helping us understand better but also leading towards improved decision-making processes within financial domain.

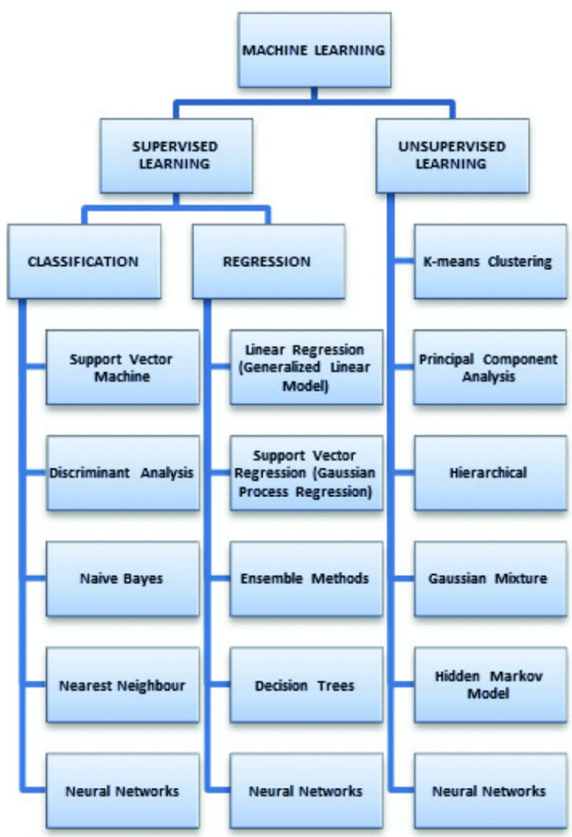

Figure 3-3: Supervised learning in Machine learning [24]

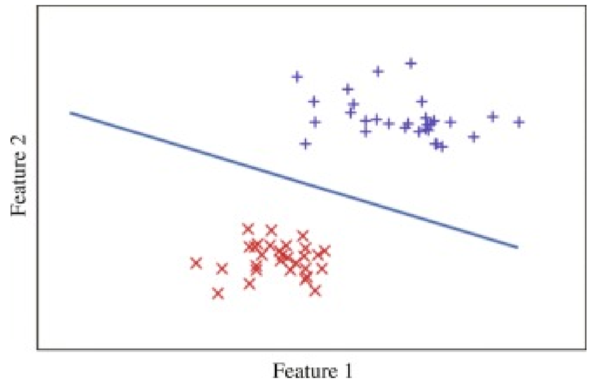

Figure 3-4: Classification problem in supervised learning [24]

3.5.2 Machine learning and Deep learning in classification problem

When we are talking about classification problems in the field of artificial intelligence, it is very important to understand deeply the comparative advantages and bounds of machine learning (ML) versus deep learning (DL). This analysis separates the main characteristics, possible uses and basic difficulties linked with each method. It offers a solid viewpoint for their application in dealing with classification duties.

ML algorithms, known for their variety and flexibility, have been taking care of classification problems since a while. Algorithms like support vector machines, decision trees and k-nearest neighbors provide strong solutions in different situations. The major benefit of ML is its capability to be understood; models such as decision trees make it simple to extract decision rules which can be very helpful in areas where comprehending the logic of a model is as important as how well it predicts outcomes. Also, the capacity of ML models to work well even with somewhat small data sets deals with situations where getting data is hard or expensive. Yet, the need for lots of feature engineering remains a big disadvantage that typically demands domain knowledge and more computational power. Additionally, ML algorithms might face difficulties due to the curse of dimensionality which means that they do not perform efficiently when the size of feature space increases.

On the other hand, deep learning - a part of machine learning that takes cues from how human brain works - has also changed this area by dealing with complex and

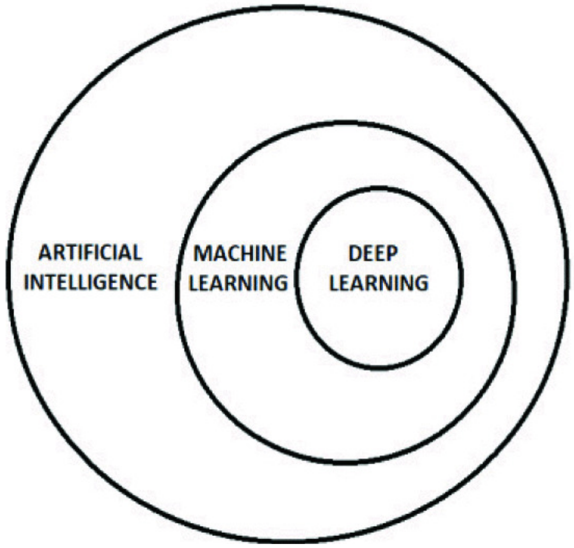

Figure 3-5: Deep learning - a subset of Machine learning [24]

high-dimensional data better. The main characteristic of deep learning, especially seen in CNNs and RNNs, is its automatic feature extraction. This feature not only reduces the need for manual work in creating features but also improves model's ability to recognize subtle and abstract patterns within the given data. Another important property of deep learning is its scalability. This means that as more data becomes available, models can also improve their performance. This kind of scalability is very important in the time of big data where there might be a large amount of information to handle. However, the need for a lot of training data and the high computational resources needed to train deep learning models are quite challenging. Moreover, in many cases the deep learning models are like "black box" where it is not easy to explain how they make decisions. This can be very important for industries that need clarity about why a certain choice was made.

The use of CNNs to turn financial indicators into visual forms shows the creative progress made possible through deep learning. This way, not just adds more easy understanding and reach to finance data analysis but also brings a change in method, giving an active and natural way for market study. But this process of transformation, which includes making numbers normal and then scaling them up or down, needs careful attention to keep the pictures that are created trustworthy and useful.

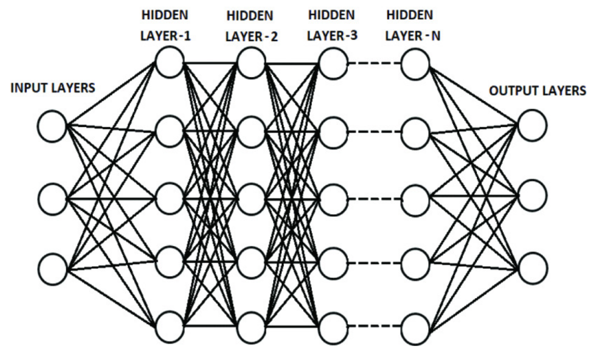

Figure 3-6: Neural networks in deep learning [24]

To end, the choice to use machine learning or deep learning in handling classification problems relies on a strategic understanding of the problem's context, data accessibility, computational power and need for model explanation. As this area progresses, there is an ongoing improvement and adjustment of these technologies which can enhance their usefulness and effectiveness in solving more varieties of classification difficulties.

3.5.3 Support Vector Machine

Support Vector Machines (SVMs) hold an essential place in the field of financial forecasting. They are good at dealing with complex market data. SVMs work based on finding a best hyperplane that increases the gap between diverse classes, a characteristic which is very useful for understanding subtle trends in financial markets.

SVMs excel in their mapping data input with higher-dimensional space. This allows them to classify the data points well, even while dealing with complex scenarios. The main parts of SVM are called support vectors, very important part of the model that actually seperates data points that lie nearest to the hyperplane and help guide model towards achieving best possible separation.

Financial forecasting enjoys SVM's flexibility, aided by different kernel functions such as linear, polynomial and RBF. This assists the model in handling various kinds of data structures. The hinge loss function that is essential to SVM can be shown as:

$$L(y) = \max(0, 1 - y_i(w \cdot x_i + b))$$

is chosen as the loss function. This highlights the importance of correctly classifying all data points and penalizes any mistakes made by our model, which helps to keep it robust.

To make SVM work well in finance-related situations, the choice of kernel functions and adjustment of parameters is very important. This careful fine-tuning is necessary for precise predictions and classification by the model, making SVM an essential tool of financial analysis.

Using SVM in the classification of financial analysis, professionals traders gain more indepth understanding about market changes. This helps to create predictive models that are precise and also have a certain level of interpretability needed for making strategic decisions in finance.

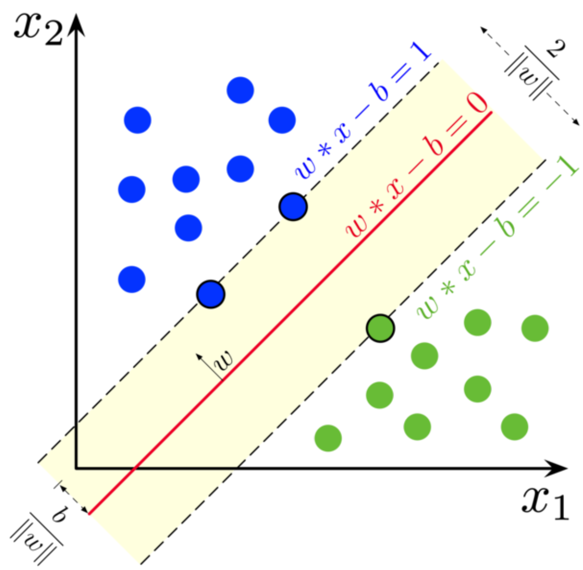

Figure 3-7: SVM [18]

3.5.4 Random Forest

Random Forest is a powerful machine learning model that identifies subtle differences in data input. It builds several decision trees while it learns and then gives the most frequent class (for sorting) or average prediction (for estimating) from these trees. The method adds random selection of different features when making splits in the tree, helping it not get too fitted just to one example compared with a single decision tree.

The method used in Random Forest is simple but very effective. It makes a "forest" made up of many decision trees, often taught using the "bagging" technique. Every tree is constructed using various subsets of data and characteristics, leading to diversity within the trees. This creates a model that can identify many patterns and unusual points in the dataset.

In predicting money matters, Random Forest is good because it works well with big amounts of data and many factors. It doesn't easily make mistakes by fitting too much, and it can understand complicated connections between things that change. This makes it very suitable for guessing the prices of stocks, directions in which markets move or signs of how the economy might do.

To assess performance, Random Forest applies measures such as Mean Squared Error (MSE) for regression and Gini Impurity for classification. Gini Impurity calculates the mix-up in a group of items and is reduced during the building of the tree. On the other side, MSE measures how much the forecasted numbers differ from real ones in regression jobs to help the model make closer predictions.

The Gini impurity for a set of items is defined as:

$$I_G = 1 - \sum_{i=1}^{n} p_i^2$$

Overall, Random Forest's versatility and robustness make it a powerful tool for financial analysis, providing insights that can guide strategic decision-making and investment strategies.

3.5.5 Convolutional Neural Network

Convolutional Neural Networks, or CNNs for short, belong to a category of deep neural networks that are very good at doing things such as recognizing and classifying

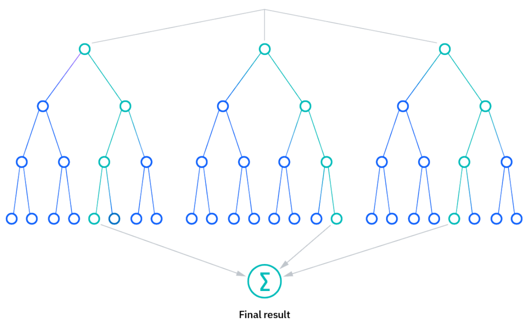

Figure 3-8: Random Forest [19]

images. They work similarly to the human eye's vision processing area by using layers called convolutional layers to find patterns, lines, and textures in pictures all by themselves.

A usual CNN structure is made up of layers for convolution, pooling and fully connected ones. The layer with convolutions uses different filters on the input to produce feature maps that show various parts of the input in detail. Pooling layers make the size of feature maps smaller so the network can pay attention to key features. Then, fully connected layers bring these features together for making final guesses.

CNNs work well when the position of patterns or features changes in different examples. For example, in predicting finance, CNNs can examine data over time and change it into a type where how things are placed matters a lot, such as with charts that show prices going up and down, to guess what will happen next.

In CNNs, loss functions like cross-entropy loss help to check the difference between what is predicted and the real labels which direct how the network learns. Cross-entropy loss is often chosen for classification jobs because it calculates how much two probability distributions vary from each other - these are predictions made by the model compared to true outcomes.

To sum up, the strength of CNNs lies in their skill to pull out features from data by themselves and in layers. This is very useful for difficult jobs such as predicting financial trends because they can detect fine details within market information that help with making forecasts and planning actions.

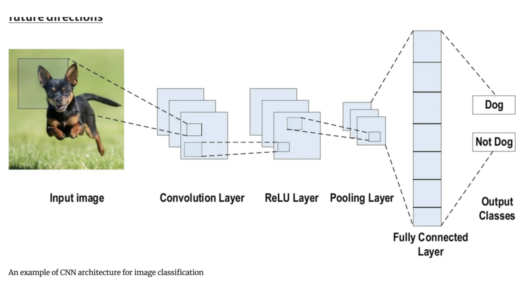

Figure 3-9: CNN [20]

Chapter 4

Results

In this section, results of the trading are shown and examined from trading simulations that are built on predictive models. The trading results are shown in an easy-to-understand way, giving a clear picture of how well every model performed over specific testing time. A comparison summary comes after which systematically assesses strengths and weaknesses for each model against others. This comparison helps to understand which models are useful for trading in reality, showing how well they perform with success rates, money-making ability and risk aspects. The examination not only confirms the theoretical abilities of these models but also gives useful knowledge about their usefulness and effectiveness in live trading. This detailed study assists in creating a strong foundation for future trading plans, directing the growth of predictive models that are more precise and polished for finance markets.

4.1 Trading returns

The Table I presents a comparative analysis of different models used for predicting the prices of various stocks, along with their total returns on investment. The setup of the experiment was done in the time range of 2007-2016. The raw data was formatted as Open, High, Low, Close, Volume of the date for each individual stock. After the training phase, the models were given pseudo 1000 USD to trade on the days that they labeled as "Buy" or "Sell", and at the end of period Return on Investments

(ROI) was calculated. These models include SVM, Random Forest, CNN-TA[23], BaH, Sezer[22], ResNet[23], alongside the proposed approach with different labeling approach. The average performances of these models across the listed stocks provide a broad perspective on their predictive capabilities and investment returns.

4.2 Comparative Analysis by Model

4.2.1 Random Forest

Random Forest gave a good general result, scoring an average of 11.075 which places it in the middle among other models we examined. This method of group learning is robust and capable to handle too much fitting, resulting in steady but not always top results. It worked very nicely with the stock AXP, getting 22.38 as its highest prediction that was quite impressive. This reveals that Random Forest has the capacity to discover intricate patterns in specific stock data sets, perhaps due to the fact that it merges numerous decision trees and thus enhances forecast accuracy. On the opposite end, its success rate with CAT at 3.81 was not very impressive which suggests limitations in model's generalization ability based on stock data characteristics and market dynamics.

4.2.2 SVM

Support Vector Machines (SVM) worked in a comparable manner to Random Forest with an average of 10.93. It showed good power in sorting and estimating, particularly when handling numerous features. The SVM gave strong results across different stocks, showing a significant accomplishment with AXP by achieving an 18.45 score which indicates the SVM can recognize patterns in how stock prices change well. However, for stocks like CAT that only scored a 3.61, this was actually the worst result of SVM. The difference shows how sensitive SVM is when you select the kernel and tune its parameters, impacting its capability to predict various stock performances accurately.

Table 4.1: Comparison of Stock Price Prediction Models

Stock	**R.Forest**	**SVM**	**CNN-TA**	**BaH**	**Sezer**	**ResNet**	**Proposed appr.**
AAPL	10.03	9.95	11.37	26.42	37.83	48.55	52.23
AXP	22.38	18.45	25.05	4.25	8.77	66.39	60.36
BA	6.12	5.97	7.03	8.6	19.04	37.87	41.27
CAT	3.81	3.61	4.33	7.19	10.96	41.13	39.35
CSCO	9.38	9.32	10.02	2.76	14.67	43.09	45.18
CVX	13.99	12.98	14.91	8.67	10.01	39.9	36.51
DIS	11.98	12.51	13.97	13.14	12.43	41.67	42.63
GE	9.17	9.04	10.35	2.17	17.52	36.08	30.08
GS	5.48	5.68	6.18	2.35	5.86	47.86	38.61
HD	13.24	14.32	15.2	15.91	28.49	35.18	40.72
IBM	7.37	7.15	8.15	7.77	17.17	24.67	31.7
INTC	10.5	11.2	11.87	8.99	18.73	41.19	47.21
JNJ	11.32	12.28	13.45	9.01	12.43	16.64	18.86
JPM	12	11.55	12.79	8.25	19.72	53.83	45.12
KO	9.78	9.51	11.113	8.85	10.03	22.98	31.83
MCD	16.33	15.87	17.94	14.43	20.17	29.09	25.06
MMM	9.81	9.83	10.88	11.36	12.21	33.05	37.49
MRK	14.44	14.01	15.93	6.55	13.47	38.3	40.67
MSFT	11.76	11.53	13.43	9.95	18.73	38.04	44.83
NKE	16.71	16.9	18	17.1	18.86	47.11	45.39
PFE	6.99	7.13	8.07	6.51	13.82	21.08	34.59
PG	9.11	8.38	9.79	5.72	7.54	15.27	20.54
TRV	15.07	15.94	17.34	12.01	15.38	42.73	39.86
UNH	8.97	8.97	9.74	13.21	22.22	48.38	45.85
UTX	8.33	8.38	9.36	7.67	16.51	34.53	39.77
VZ	8.93	9.62	10.23	9.29	11.33	22.38	29.48
WMT	13.89	13.72	15.2	6.28	17.83	23.75	31.13
XOM	13.21	12.43	14.51	4.78	14.68	37.97	34.17
Average	*11.075*	*10.93*	*12.36*	*9.25*	*15.94*	*36.739*	*38.23*

4.2.3 CNN

The CNN, that makes use of the levels of space in data, displayed an average result of 12.36 and showed its skill in locating important designs from how stock prices change. The top performance was seen with AXP where it reached a score of 25.05. This points out that CNN can recognize intricate patterns because it possesses numerous layers within its structure. However, in its examination of CAT, where it received a 4.33 score, it was not as impressive. This implies there might be challenges for the AI to adapt its pattern identification skills to specific market data features or how stocks behave.

4.2.4 BaH

The BaH strategy, a basic standard we compare with, had the smallest average score of 9.25. Because it's not active and its top performance was much less compared to predictive models; for AAPL stock, its maximum was only 26.42 showing that there are times when owning a stock which performs very well naturally brings large profits without needing much action. However, using this method only resulted in a ratio of 2.17 for GE. It reveals the risk involved when stocks are not managed properly during unfavorable market situations.

4.2.5 Sezer

Sezer's predictive capabilities had a mean score of 15.94, It had best results when dealing with AAPL, hitting 37.83 which indicates they have a good plan or method that fits nicely with how prices move for some stocks that do well. But its method for GS with just 5.86 as the score is one of lesser results suggesting there might be limits to how well the model can adjust or predict in different market situations.

4.2.6 ResNet

ResNet, having a value of 36.73, shows excellent average performance due to its deep learning structure which can comprehend complex and subtle patterns in information.

This model performed very well on AXP stock - it is possible that the stock's past behavior matches nicely with ResNet and might notice complex patterns that simpler models do not see. However, the results for GE shares were not as impressive which suggests there are parts where even sophisticated systems like ResNet could find difficult to perform accurately in this area of analysis.

4.2.7 Proposed approach

The proposed approach has a mean result of 38.23, which indicates that it works very well in forecasting what will occur in the stock market. The performance is even better when working with AAPL stock; this signifies that our model's way of operating is particularly suitable for comprehending how prices change for AAPL in the market. Nevertheless, the forecast about GE shares was not as strong, highlighting certain difficulties or issues encountered by the model with certain kinds of stocks or market situations.

4.3 Summary of results

In this detailed study, we look at and contrast the effectiveness of different predictive systems for predicting stock market trends. We are looking at multiple models like Random Forest, Support Vector Machine or SVM, Convolutional Neural Network that is used for Technical Analysis which people call CNN-TA, also the strategy called Buy and Hold - BaH for short - Sezer model as well as ResNet and one approach we have come up with ourselves. The comparison looks at their usual performance numbers over different stocks, concentrating on what these outcomes mean for making predictions in the stock market.

The approach we suggest shows the best average performance, with ResNet not far behind. This means both methods are very good at using patterns and trends in stock prices to their advantage. The success of our approach hints that its method, while not detailed here but likely includes new or complex parts, fits well with the complicated nature of financial information. In the same way, ResNet performs very well because it has a deep learning structure. This is famous for learning different levels of representations and understanding complex patterns in data.

On the other side, the BaH method that we use for comparing as a standard passive investing way has shown to have the least average success. This result points out how important it is to use active prediction models if you want to improve investment methods because even simple predictive systems like CNN-TA and Sezer are better than BaH strategy, showing that there can be benefits when using basic forecast algorithms in analyzing stock markets.

Random Forest and SVM show average performances that are quite similar; they do not perform as well as the best methods but still better than doing nothing. This similarity could mean that even though these models work in different ways, they can both understand the forecasting signs in their given data to a similar extent. The method of Random Forest uses many decision trees together to decrease overfitting and make better predictions, while the SVM is good at identifying the best boundary between different groups. These techniques both give useful information about what could happen next in the market.

The CNN-TA method, made to use time and space patterns in data, has a performance that's not the best but still shows how useful convolutional neural networks can be for looking at financial trends over time. How it is built to imitate human visual information processing gives a different perspective on how markets move.

To sum up, this comparison study shows there are big differences in how well various forecast methods work when looking at predicting the stock market. The better results from our suggested method and ResNet indicate that deep learning and maybe more complex techniques could be very promising for use in financial studies later on. Nevertheless, the somewhat small but important roles of models such as Random Forest and SVM support the thought that having a varied set of tools and a detailed knowledge about what each model does well or not so well is very important for good predictions in finance. The results suggest choosing prediction models with care, picking ones that fit the particular details of where you want to invest and also match the nature of the financial information you are using.

Chapter 5

Conclusion

5.1 Sumary

In the research paper, we have looked into how machine learning, data science and financial study can work together. The main focus was on using Convolutional Neural Networks (CNNs) to predict market movements in a short-term manner. It seems that there are missing parts in current ways of investing, especially when it comes to using different kinds of data with CNNs well. The proposed approach changes technical measures into technical images so that the strong abilities of CNNs can process images for complex pattern recognition and predicting future trends in finance.

The research is supported by a thorough review of many written works, placing the new method in the larger story of strategies for investing money. It had been researched far more than just CNNs in this paper and compared different machine learning models like Random Forest and SVM, as well as sophisticated methods such as ResNet. This comparison showed the unique strong points and weak spots of each model, giving a detailed view of how they can be used in predicting financial outcomes.

The research shows that the proposed method and ResNet work better at understanding the complicated patterns of stock market movements, highlighting how useful deep learning could be in this area. At the same time, classic models such as Random Forest and SVM showed they can predict well sometimes but not always for various stocks.

To finish, the study helps potential investors know more about using CNNs and different ways of machine learning to analyze finance. It is suggested that we should use more variety in data transformation so that the neural network models work best. The proposed approach has good outcomes, and when its results are compared to other models, it makes a strong base for later studies and real-world uses in predicting financial markets.

5.2 Critique and future work

The paper gives a wide analysis of using machine learning and deep learning models for predicting financial activities. Although the research has shown substantial outcomes by showing the capability of these models to understand complicated financial details, it is important to recognize that there are limitations in the current approach, one being absence of sentiment analysis within present methodology. The addition of sentiment analysis could improve the ability to predict market movements, as emotions from investors play a crucial part in shaping market trends. The joining together of sentiment analysis, especially from news sources, social media and financial reports might offer a more comprehensive understanding of the market. Such addition could possibly improve how well the models used for prediction work.

Besides, although the performance metrics shown in this thesis are good, there is an essential conversation about the ability to maintain these results. Financial markets are always changing due to many factors that affect movements every second. A model which does extremely well under presented market situations might not continue showing similar levels of precision over time - especially if dynamics within those markets change too. This brings up queries regarding the models' strength and flexibility to handle major fluctuations in the market.

Another point is thinking about the market effect when these models are used for actual trading. The study does not talk about what could happen if a lot of people start using this method to trade in big amounts. In real life, when many people buy or sell according to the model's predictions, it might cause changes in market prices. This could slowly lessen the strategy's success rate over time. This is especially relevant to algorithmic trading, where trades with high volumes using comparable predictive models could cause market inefficiencies.

For forthcoming research, there is a need for a detailed and comparative study of deep learning models with machine learning models. This is important to identify the areas where each of these methods performs better or worse. In that study, it is planned to compare the performance of different machine learning techniques to deep learning methods in a range of financial prediction situations in an organized manner. We hope that by doing direct comparisons, this investigation can reveal the unique conditions and market movements where each model type shows better prediction precision. This means it is a must to test the two groups of models in different levels of market instability, complexity of data and time periods to find out what they are good at and their limits. This detailed comparison will not only assist us in selecting the best model for a particular forecasting job based on its needs but also offer useful guidance about modifying model structures for better performance in specific situations. This effort will play an important role in improving predictive models within finance, making sure that selected models are strong enough and match well with unique features found within a given financial setting.

On top of that, it might help to show the results not just as annual Return on Investment (ROI) percentages but also in real dollar values. This change could give a more concrete comprehension of how much money is involved when talking about model performance. Adding particular monetary details might greatly improve understanding for people reading this who aren't so skilled with finance measurements or know well what ROI means.

For the future work, it is very important to check how sentiment analysis can be combined with present models. This has possibility to give a more complete method for financial forecasting. Also, we need to look into the long-lasting performance of our model and how well it handles changes in market conditions over time. Finally, we should understand what could happen if these types of models become widely used in real-life trading situations so as not only determine their feasibility but also sustainability under those circumstances. These ways of exploration don't just assure to boost the strength and use of the study, they also give something substantial to wider discussion about how complex computer-based models relate with financial market changes.

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