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Using Artificial Intelligence to Forecast Stock Markets

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ABSTRACT:
This thesis examines the application of AI in stock market forecasting by comparing the performance of several AI-based models to traditional forecasting approaches. The study evaluates how AI models, such as Support Vector Machine (SVM), Artificial Neural Network (ANN) and Long Short-Term Memory (LSTM) can overcome the limitations of traditional models, which often rely on assumptions of market efficiency, linearity, and rational investor behaviour. These assumptions frequently fail in modern, volatile, and non-linear financial environments.

This thesis concludes that AI is not just a supportive technology but a critical component in the evolution of stock market forecasting and portfolio management. AI models enable real-time adaptability and improved decision-making in environments characterized by uncertainty and rapid change. As financial markets continue to evolve, the integration of AI with domain knowledge and alternative data sources will shape the next generation of intelligent financial systems.

KEYWORDS: Stock Market Forecasting, Artificial Intelligence, Machine Learning, Deep Learning, Support Vector Machines, Artificial Neural Networks, Long Short-Term Memory

Contents

Tables

1 Introduction

Forecasting the stock market is considered a difficult aspect of financial time series analysis due to its inherently dynamic, nonlinear, complex, nonparametric and chaotic behaviour (Kara et al., 2011). Investors aim to identify winning stocks when making investment choices. Monitoring the stock market is increasingly difficult because of the large amount of information that is available. Many factors need to be considered when predicting share prices, including historical stock prices, volume and many other indicators. These variables are used by investors when making analysis of a stock to predict its future price.

Investors have been trying to predict stock prices for a long time by using different models and theories to maximise their returns. The two traditional theories that investors have used to forecast stock prices are Efficient Market Hypothesis (EMH) and Random Walk Hypothesis (RW). However, both models have been heavily criticized by economists regarding their validity, particularly due to the presence of various market anomalies. For that reason, economists have created Inefficient Market Hypothesis (IMH). The IMH states that markets are not efficient, do not consistently follow a random walk and there is inefficiency in markets (Asadi & Others, 2012). The IMH is one example of models that tries to predict stock markets which was developed with help of AI.

As mentioned earlier, two traditional theories that are used in forecasting stock prices are Efficient Market Hypothesis (EMH) and Random Walk Hypothesis (RW). The usability of these theories has been criticised in the wake of stock market changes. These models assume market rationality and rely heavily on linear assumptions (Fama, 1970). However, these models struggle to account for the complex, nonlinear, and dynamic nature of real-world markets, especially in the face of large volumes of unstructured data like news sentiment and social media trends.

Recent advances in artificial intelligence (AI), particularly in machine learning, have introduced powerful new tools for stock market forecasting. AI-based models, such as Deep Neural Networks (DNN) and Long Short-Term Memory (LSTM) networks, are capable of processing large and complex datasets, capturing nonlinear relationships, and extracting relevant features from raw data (Chong et al., 2017). These capabilities allow AI models to overcome many of the limitations inherent in traditional forecasting approaches.

In practice, AI systems have supported investors by enabling more accurate and automated decision-making, assisting in expertise modelling, and performing complex tasks that would be too time consuming or difficult for human analysts to execute (Chen et al., 2005). For example, deep learning models can uncover hidden patterns and interrelationships in data that surpass the analytical capabilities of traditional methods or individual investors (Najem et al., 2024). These capabilities allow AI to enhance the accuracy of market forecasts while also expanding the range of analytical tools available to contemporary investors.

While AI brings benefits to investors when making investment choices, AI still has limitations when making predictions. Many studies have shown that AI still lack the capability to generate consistently accurate forecasts. Lin & Lobo Marques (2024) state that many models use limited data sources and fail to integrate social media, financial news and macroeconomic data, reducing prediction accuracy. There is also a lack of automation in selecting the best technical indicators. Combining different data types for example numerical, textual and sentimental is challenging and model performance often varies across regions. Moreover, most models struggle to account for external influences like government policies and consumer behaviour, which significantly affect market trends.

This study addresses this gap by examining how AI-based forecasting models differ from traditional models in terms of methodology, data processing and predictive performance. The research also investigates whether AI can provide investors with a superior advantage in stock market forecasting. By exploring these questions, the study aims to contribute to a more nuanced understanding of AI's practical value in financial prediction and its implications for investment decision-making.

1.1 Purpose of the Study

This study investigates how AI can be used to forecast stock markets and what kind of advantages it may offer to investors compared to traditional models. While AI-based models such as neural networks and deep learning algorithms have shown promising results in their capability to automatically extract relevant features from large volumes of raw data, eliminating the need for predefined predictors and effectively capturing the market's complex, nonlinear dynamics, the existing literature lacks a comprehensive comparison between AI-based models and traditional forecasting frameworks, such as those based on the Efficient Market Hypothesis (EMH) or Random Walk Theory (RW) (Chong et al., 2017; De Faria et al., 2009). Additionally, many prior studies rely on specific AI techniques in isolation and do not clearly identify the conditions under which AI models outperform traditional methods. Therefore, the literature does not yet fully explain when and why AI adds value in practical forecasting scenarios.

Research Question: How can investors gain a superior advantage in stock market forecasting by using AI models and how AI models differ from traditional forecasting models?

The motivation for this research stems from the growing relevance of AI in financial markets and its potential to improve stock market forecasting. While AI-based models such as neural networks, support vector machines, and deep learning techniques have shown promising results in previous studies, it remains unclear whether these models consistently offer superior predictive power compared to traditional approaches based on the Efficient Market Hypothesis (EMH) or Random Walk Theory. This study aims to assess the usability and effectiveness of AI-based forecasting models, particularly in terms of their ability to deliver more accurate and timely predictions than conventional models. Furthermore, the study explores how AI models differ methodologically and practically from traditional forecasting techniques. If AI-based models can be shown to consistently outperform traditional models, they may represent a paradigm shift in how investors approach market prediction and risk management.

Better understanding of the capabilities and limitations of AI models can support investors in making more informed decisions, optimizing portfolios, and managing risk more effectively. This research builds on existing literature while aiming to fill identified gaps.

1.2 Structure of the Study

This study is structured as follows: Introduction section reviews the information on AI and traditional stock market forecast methods, followed by an explanation of the purpose and the research question of the study. Second chapter will focus on traditional models and hypothesis that are used to forecast stock market movements. Subsequently, third chapter of the study focuses on different AI models that have been used in forecasting stock markets. Study will focus on machine learning and deep learning models. In the fourth chapter, the study discusses about limitations that occurs in the usage of AI in stock market forecasting. Fifth chapter focuses on performances of different AI based models in forecasting. Study also shows how AI based models' performance compared to traditional methods. Lastly, the sixth chapter concludes most relevant findings of the study. The study ends with the list of references in the end.

2 Theoretical Framework

Investors, analysts and financial institutions use various models and theories to forecast stock market movements. The purpose of the models is to study the past movements and prices of stocks and use the data to try to identify patterns that may help predict future trends. Theories are used to understand how markets should move and when. This section examines these models and the financial theories that are used to analyse stock prices.

2.1 Efficient Market Hypothesis (EMH)

Market efficiency has been studied since the early 1900s by Louis Bachelier, the current concept of EMH was coined by Eugene Fama in 1970. According to the EMH, all known information about the stock is reflected in the stock price and the new information is immediately reflected in the stock price (Fama, 1970). Additional common assumptions are that investors behave rationally, trading is frictionless, markets are sufficiently liquid, and any chance to earn an arbitrage profit is absent (Fama, 1970). EMH can be divided into three different variants: weak form, semi-strong form and strong form. In weak form, the assets price incorporates all historical information. Semi-strong form also reflects all previous information in the asset prices, in addition all public information as soon as it becomes public. Strong form incorporates both previous and new information as well as any insider information (Fama, 1970). According to these forms, the market cannot be beaten except by insider information or pure luck. (Fama, 1970). This would make it almost impossible, if not impossible, to forecast the stock markets.

Although the EMH offers a straightforward framework to forecast the behaviour of financial markets, the market contains many anomalies that the theory cannot explain. For example, investors do not always act rationally in financial markets, which can lead to market bubbles, overreactions or underreactions, suggesting markets are not perfectly efficient. These anomalies can therefore be exploited to forecast stock market movements by identifying non-random patterns in market behaviour.

2.2 Random Walk Theory (RW)

The Random Walk Theory states that all securities perform "random walk", meaning all future prices of securities do not follow any patterns and are random. RW asserts that the current market price is the most accurate reflection of future market prices, with any deviations resulting from unpredictable, non-deterministic factors (Jensen & Benington, 1970). This makes forecasting future stock prices impossible according to RW. For example, if a stock asset follows a random walk, its value at any given period will be the same as its value in the previous or next period, adjusted by a random variable or disturbance (Jensen & Benington, 1970). RW can be closely related to efficient market theory. RW is closely linked to the weak form of the EMH, as it suggests that the current stock price already reflects all historical price information. In a market that follows a random walk, prices rapidly adjust to new internal and external information, making it nearly impossible to react fast enough to gain an advantage (Jensen & Benington, 1970). Although RW claims that forecasting stock markets is impossible, similarity to EMH, various anomalies create market inefficiencies, allowing investors to predict the financial markets with various patterns and technical indicators. While there has been much controversy about the practicality of RW, RW theory remains a foundational concept in financial economics.

2.3 Statistical – and Econometric Models

Statistical and econometric models, such as ARIMA, GARCH, and classical regression techniques, have long been used in stock market forecasting. These models represent some of the earliest data-driven approaches to financial time series analysis. ARIMA (Autoregressive Integrated Moving Average) is a statistical method used for time series forecasting, particularly in financial markets. It extends the ARMA (Autoregressive Moving Average) model by incorporating an integration (I) component to address non-stationary data, such as stock prices (Bao et al., 2025). ARMA itself combines two components: the autoregressive (AR) part, which captures the linear relationship between current values and their past values, and the moving average (MA) part, which models the correlation between forecast errors (Bao et al., 2025). ARIMA enhances this approach by applying differencing to stabilize the time series, making it suitable for modelling more complex and dynamic financial data (Bao et al., 2025). As a result, ARIMA provides a flexible and widely used statistical framework for capturing trends, seasonality and autocorrelations in stock price movements.

While the ARIMA offers enhanced adaptability in modelling the complex dynamics of stock price time series, ARCH is a widely used econometric model, that accounts for conditional heteroskedasticity by modelling how today's stock price volatility is influenced by previous periods, effectively capturing the typical clustering pattern seen in financial time series (Bao et al., 2025). The Generalized Autoregressive Conditional Heteroskedasticity model (GARCH), builds upon the original ARCH framework by introducing a more flexible structure that reduces the number of parameters needed for estimation (Kim & Won, 2018). Financial time series often demonstrate a phenomenon known as volatility clustering, where periods of high volatility tend to follow other volatile periods, and calm periods tend to persist. Moreover, these financial datasets frequently exhibit leptokurtosis, meaning their probability distributions tend to exhibit extreme values more frequently and are more sharply peaked than those of a normal distribution (Kim & Won, 2018). Both ARCH and GARCH models are effective in capturing these features, particularly the persistence in volatility and the non-normal distribution of asset returns.

Despite their popularity, these traditional models rely on strict assumptions. Linearity, normal error distributions and stationarity are frequently violated in modern markets exhibiting pronounced non-linearities and regime shifts. Recent developments in integrating AI to these models have enhanced the forecasting power of these models.

Studies indicate that a hybrid model that integrates ARIMA with support vector machines (SVM) delivers the highest forecasting accuracy and generates the most favourable investment returns (Bao et al., 2025). In this model, ARIMA is used to capture linear models and SVM is employed for capturing nonlinear patterns (Bao et al., 2025). Kristjanpoller & Minutolo (2016) combined an artificial neural network (ANN) with a GARCH framework to forecast oil price volatility. By incorporating supplementary inputs, such as market indices and relevant exchange rates and selecting architecture tailored to various volatility horizons, they showed that the ANN–GARCH approach outperformed a standalone GARCH model, reducing forecast error by roughly 30 %. These studies suggest that while ARIMA and GARCH provide a solid theoretical foundation, AI-enhanced hybrids better accommodate non-linearity and complex volatility dynamics.

2.4 Capital Asset Pricing Model (CAPM) and Fama-French Three-Factor Model

The Capital Asset Pricing Model (CAPM) got first introduced in 1964 by economist William Sharpe. CAPM explains the expected return of an asset based on its systematic risk, represented by the asset's beta coefficient. The model assumes that investors are rational, markets are efficient and that only non-diversifiable market risk should be rewarded with a risk premium (Sharpe, 1964). The model provides a logical framework aligning with traditional financial theory, linking expected return linearly to systematic risk. Fama and French (2004) argue that although the CAPM seeks to explain the relationship between an asset's expected return and the return of the market portfolio, the model has been criticized for relying on unrealistic assumptions, such as a single investment period and the ability to borrow or lend unlimited amounts at the risk-free rate. The assumptions of CAPM, such as investor rationality, market efficiency, and a linear risk–return relationship often fail to capture the complexity and unpredictability of stock price movements in modern financial markets.

Eugene Fama and Kenneth French (1993) introduced the Fama-French Three-Factor Model, which extends the traditional CAPM model by adding two additional factors to explain anomalies that the CAPM cannot explain. The two factors that Fama and French added to the CAPM model are size and value. The size factor consists of the performance differential between small-company equities and large-company equities (SMB, small minus big), and the value factor consists of the discrepancy in returns between high book-to-market equity portfolios and low book-to-market equity portfolios, known as the HML component (high minus low) (Fama & French, 1996). (Fama & French, 2015) introduced an updated version of their original three-factor model, known as the Five-Factor Model. The new model adds two additional factors: profitability and investment patterns. This extension was proposed because the original three-factor model failed to account for several return anomalies observed in empirical research.

Both the CAPM and Fama-French Three-Factor Model are built on the assumptions of market efficiency, investor rationality, and linear relationships between risk and return. Given these limitations, AI can serve as a valuable complement to traditional asset pricing models by identifying additional explanatory factors, capturing nonlinear patterns, and adapting to dynamic market environments.

2.5 Statistical Learning Theory (SLT)

Statistical Learning Theory (SLT) provides a framework for understanding how models can learn effectively from limited data. The central principle of SLT is to design learning algorithms that account for finite sample constraints while still maximizing their ability to generalize to unseen observations (Ha & Tian, 2008). In doing so, SLT offers a solid mathematical foundation for small-sample statistical learning and guides the development of algorithms with proven strong generalization performance (Ha & Tian, 2008). SLT forms the foundation for regression techniques, which are used to identify a model that describes the relationship between the variables. Regression analysis examines how one or more predictor variables affect a response variable and quantifies the strength of that influence (Miller et al., 2022). Two SLT-based regularization techniques that are particularly common in high dimensional finance applications are Lasso Regression and Ridge Regression.

The Least Absolute Shrinkage and Selection Operator (Lasso) is a regularization technique for regression problems with many predictors. Lasso regression applies an L1 norm, the sum of absolute coefficient values to the ordinary least-squares loss (Miller et al., 2022). This penalty shrinks coefficient estimates toward zero, driving many of them exactly to zero when the penalty is large enough. As a result, Lasso automatically removes irrelevant predictors and produces a sparse, simpler model with only the most influential variables (Miller et al., 2022). In practice, Lasso extends standard linear regression by introducing a shrinkage mechanism where the shrinkage is determined by the shrinking of vector values that draws coefficient estimates toward a central value, which is usually zero and thereby reducing model complexity (Miller et al., 2022)

Ridge regression is a type of linear regression that incorporates an L2 regularization term into the standard sum-of-squares error function. This regularization helps to balance the trade-off between bias and variance, improving model generalization (Zhang et al., 2015). The method is used to uncover linear relationships within the dataset (Zhang et al., 2015). Ridge regression, much like Lasso, aims to create a more concise model by addressing multicollinearity and reducing the influence of correlated predictor variables. This method uses L2 regularization, introducing a penalty term based on the square of the coefficients (Zhang et al., 2015). Unlike Lasso L1 regularization, which can reduce some coefficients to zero, L2 regularization retains all coefficients simply shrinking them toward zero. (Zhang et al., 2015) As a result, ridge regression produces a more complex model with no zero-valued coefficients. The shrinkage is computed using a specific estimator known as the ridge estimator.

SLT provides the bias–variance trade-off and capacity control that underpin many modern machine learning algorithms. By regularizing models and selecting relevant predictors, these techniques enable robust and generalizable forecasts, making them essential tools in today’s data driven financial forecasting.

3 Literature Review

There are two types of models that are used to forecast stock markets. They are classified into linear and non-linear models (Rather et al., 2015). In this study, we focus on non-linear models, which include models that are based on AI such as Artificial Neural Networks (ANN) and Support Vector Machines (SVM). Kim & Han, (2000) and Armano et al., (2005) stated that non-linear models can overcome the limitations of linear models as non-linear models can capture non-linear pattern data, thus improving the performance of stock forecasting. This section explores the application of AI-based models in stock market forecasting, with the aim of examining their effectiveness and advantages over traditional linear approaches.

3.1 Machine Learning (ML)

Machine learning (ML) is a field of study in artificial intelligence. Machine learning techniques analyse historical data to identify patterns through a process called training or learning. These patterns are then used to make predictions on new data. (Henrique et al., 2019). According to Henrique et al. (2019), using ML has two different phases. The first phase involves selecting relevant variables and models for prediction, reserving a portion of the data for training and validation to optimize model performance. The second phase applies these optimized models to the test data, evaluating their predictive accuracy. Unlike traditional forecasting methods, ML models can handle large amount of data and different kinds of nonlinear, chaotic and complex data, leading to more accurate predictions (Kumbure et al., 2022). According to study of Nazareth & Ramana Reddy (2023), machine learning models, such as deep learning, hybrid models and ensemble models can outperform traditional finance models.

3.1.1 Support Vector Machines (SVM)

Support vector machine (SVM) was first introduced by Vapnik (1999). Support Vector Machines (SVMs) are a distinct class of learning algorithms known for their ability to control the complexity of the decision function, leverage kernel functions, and produce sparse solutions (Cao, 2003). Based on the structural risk minimization principle, SVMs estimate functions by minimizing an upper bound on generalization error (Chao, 2003). This approach makes them highly resistant to overfitting, enabling strong generalization performance in various time series forecasting applications (Cao, 2003). The two main categories for SVM are Support Vector Classification (SVC) and Support Vector Regression (SVR) (Patel et al., 2015).

The abilities of SVM make them well-suited for linear classification tasks, as it needs minimal parameter tuning, often matches or even surpasses the performance of far more complex algorithms (Bustos & Pomares-Quimbaya, 2020). SVM is used for its ability to construct an optimal hyperplane that maximizes the separation between different classes, ensuring the greatest possible margin. (Behera et al., 2023). According to the Li et al. (2025) SVM is noted for strong generalisation performance, especially when the data set is high dimensional and data sample size is limited. These abilities make SVM good in predicting time sequence, stock trend, pattern classification recognition and function regression estimation (Yang et al., 2020).

According to Gavrishchaka & Banerjee (2006), empirical studies on the S&P 500 and FX markets show that SVM-based volatility models consistently equal or outperform mainstream models, such as GARCH, across a range of out of sample windows, especially when long-memory effects, leverage asymmetry or heterogeneous trader horizons must be captured. A further benefit of an SVM-based volatility framework is its robustness to missing observations, making it well suited for handling the non-stationary nature of market data (Gavrishchaka & Banerjee, 2006). These abilities make SVM particularly effective in scenarios where, that available data is noisy or non-stationery and volatility clustering is observed.

SVMs ability to transform sentiment cues extracted from financial news articles and social media into quantitative variables and incorporate them into models that forecast stock market movements has increased the usability of the model (Gupta et al., 2025). This can improve investors analysis, particularly in the context of fundamental analysis. As discussed in section 2, traditional models and methods that tries to forecast stock market movements, models are based on the assumptions of linearity between variables. Unlike these linear regression models, which are not designed to capture non-linear relationships, SVM is highly effective in modelling complex and non-linear patterns in financial data (Gupta et al., 2025).

While usage of SVM has proven to be beneficial in stock market forecasting, several challenges remain in its usage. One of the limitations is SVMs ability to work under large amount of data due to its computational complexity and SVMs implementations demands large training time (Gupta et al., 2025). It has also been found that SVM use is failing to deliver optimal results in real-time stock market forecasting where rapid response is essential (Gupta et al., 2025). In situations where dataset is imbalanced, SVM has shown to have poor accuracy in these situations. These limitations make SVM susceptible to producing forecasts with reduced accuracy (Gupta et al., 2025). Given the vast volume and variety of financial data today, SVM is often combined with other AI techniques to enhance prediction accuracy. Furthermore, Cervantes et al. (2020) noted that one of the disadvantages of SVM usages comes from the excessive computational cost. Training SVM in large data sets can be very slow process, and this process lifts computational costs up.

A recent trend in stock market forecasting is the growing interest in hybrid AI models that combines typical deep learning models and machine learning models. By integrating two different types of AI models, the accuracy and effectiveness of stock market forecasting can enhance. Gupta et al. (2025) states that, in many workflows, a deep learning network is first employed to extract high level features from the raw text then those representations are then passed to an SVM or a logistic regression model to produce the final sentiment labels. These models have demonstrated an understanding of contexts and grammatical structures, which is useful for interpreting information in social media and news (Gupta et al., 2025)

3.2 Deep Learning (DL)

Deep learning (DL) is a key sub-field of machine learning, which has gained widespread adoption across disciplines thanks to its strong predictive accuracy and ability to learn rich feature representations (Wang et al., 2025). Deep learning is a branch of machine learning that implements artificial neural networks (ANN), computational structures modelled on the layered organisation and signal processing principles of the human brain (Awan et al., 2025). By tracing the way that the cerebral cortex extracts and combines increasingly abstract features, these networks can tackle complex pattern recognition and decision-making tasks, forming the basis for many modern intelligent applications (Awan et al., 2025). This way DL is capable of analyse and make predictions of data by using ANN.

According to Chong et al., (2017), the application of DL can enhance the traditional methods of stock market forecasting. One of the strengths of DL is its capacity to mine patterns directly from vast, unprocessed datasets, without requiring predefined explanatory variables. This property is highly valuable in stock-market forecasting where price movements depend on a tangle of nonlinear, interacting influences (Chong et al., 2017). When well documented predictive factors are available, explicitly incorporating them often yields stronger results than feeding the network undifferentiated data alone. Nevertheless, those same factors can simply be included among the network's inputs, allowing the deep learning model itself to discover how they combine with broader market information to drive price changes. (Chong et al., 2017). The abilities of DL, such as the ability to extract patterns from raw data, have proven to be very effective in many different problems and the numerous studies have shown DLs effectiveness in time series forecasting (Jiang, 2021).

As discussed in section 2, traditional models and methods usually are based on assumptions about linearity. These models work in certain situations. DL models are excelling at modelling the stock markets inherent non-linear dynamics and consequently deliver notably strong accuracy in forecasting stock market index movements (Wang et al., 2022). The non-linear behaviour of stock markets can be caused by for example investors' sentiments, economic situations and news. DL is capable to gather information and create data from these factors, making it superior compared to the traditional forecasting methods (Sharma & Shekhawat, 2022).

According to a study by Long et al. (2019) empirical evidence shows that DL approaches consistently outperform both conventional machine learning algorithms and classical statistical techniques in forecasting accuracy. The study also found that, DL models show better profitability than any other model. These results are due to DL methodologies having better capabilities to capture more profitable and stable signals from data that traditional methods. (Long et al., 2019). Also study by Jiang (2021) states that DL techniques in specific scenarios, like stock market forecasting, have shown superior performance compared to traditional models.

While deep learning models have demonstrated strong performance when applied to large-scale datasets, their effectiveness is highly dependent on both the volume and the quality of the data used. Wang et al. (2025) have divided data related challenges into four different categories: data quality, data sparsity, multi-modal data and spatial-temporal data. The characteristics of big data significantly influence deep learning performance, primarily through the mechanism of information fusion (Wang et al., 2025). Wang et al. (2025) also states that, since deep learning models cannot incrementally update knowledge and require full retraining due to data dependencies, the need for incremental learning mechanisms becomes evident, especially in dynamic decision-making environments.

3.2.1 Artificial Neural Networks (ANN)

Artificial Neural Networks (ANN) are type of a neural network. Neural networks are flexible statistical models inspired by the structure of the brain. Neural networks can adapt by learning to estimate the parameters of a given population using only small number of examples (Abdi et al., 1999). Neural network is a biologically inspired model composed of multiple individual processing units known as neurons. These neurons are interconnected through a structured mechanism that involves a series of designated weights (Moghaddam et al., 2016). More specifically, ANNs are non-linear models that learn directly from data. Because they self-organise, modify their connection strengths as learning progresses and retain learned relationships much like human memory, they excel at classification, forecasting and pattern recognition tasks (Hu et al., 2018). This data driven learning allows ANNs to uncover hidden functional relationships that would be difficult to specify with explicit equations (Hu et al., 2018).

The use of ANN for stock market forecasting is well suited due to the non-linearity of the stock market and its volatility nature. According to Vui et al. (2013), ability of ANNs to learn and recognize patterns from complex, non-linear data makes it highly suitable for applications like stock market forecasting. Additionally, ANN can adjust to data trends and the relationships between inputs and outputs, resulting in more accurate forecasts compared to traditional approaches (Vui et al., 2013). Khashei & Bijari (2010) emphasize that a major strength distinguishing ANN models from other nonlinear techniques is their proven capacity as universal function approximators. In other words, they can replicate an exceptionally broad spectrum of functional relationships with very high accuracy.

The hybrid ANN models have demonstrated superior performance compared to traditional ANN models. Khashei & Bijari (2010) introduced a novel hybrid approach of ANN, using ARIMA to yield more accurate prediction in stock market forecasting. Their empirical results indicate that using hybrid model of ANN creates more accurate prediction of time series forecasting. Patel et al. (2015) presented two ANN fusion models, first using Support Vector Regression (SVR) and second using Random Forest (FR) and SVR. The results show that incorporating SVR or RF enhance the accuracy of ANN to forecast stock markets (Patel et al., 2015). The advantage of such hybrid models lies in their ability to separate and address both linear and nonlinear components of financial time series, thereby reducing forecasting errors and improving robustness.

As discussed in section 2, traditional stock market forecasting techniques and models are unsuitable for forecasting market values influenced by external factors. In recent years, numerous researchers and financial analysts have highlighted the importance of recognizing the non-linear dynamics present in financial markets (Thawornwong & Enke, 2004). Although several non-linear statistical methods have been employed to enhance the accuracy of stock return and price forecasts, many of these approaches are model driven, requiring the prior specification of the non-linear structure before parameter estimation can take place (Thawornwong & Enke, 2004). The ability of ANN to learn the relationship inherent in the variables without pre-specification, makes it particularly effective and superior compared to conventional forecasting techniques.

According to research, while ANNs have proven to be valuable in time series forecasting, numerous studies have indicated that their performance can be negatively affected by the noisy, non-stationary, and high-dimensional nature of stock market data (Kara et al., 2011; Zhong & Enke, 2017). Due to the volatility caused by constantly changing market conditions, reflecting market variables directly in models requires some assumptions (Guresen et al., 2011). Similar to SVM and DL models, the performance of ANNs is highly dependent on the quality and relevance of the input data.

3.2.2 Long Short-Term Memory (LSTM)

Long Short-Term Memory (LSTM) was first introduced by Sepp Hochreiter and Jürgen Schmidhuber in 1997. LSTM is widely used deep learning method within Recurrent

Neural Networks (RNN), which is particularly effective for time series forecasting. It can be applied to both classification and regression tasks across various domains, including to stock market prediction (Bhandari et al., 2022). A Recurrent Neural Network (RNN) is a type of artificial neural network designed to handle sequential data. Unlike standard neural networks, RNNs have connections that loop back on themselves, allowing them to retain information from previous time steps (Jiang, 2021). However, standard RNNs often face the vanishing gradient issue in practice, where the gradients used for training either become too small or too large when the network is unfolded over many time steps (Jiang, 2021). LSTM networks were specifically developed to address this vanishing gradient issue.

According to Wang et. al. (2022), LSTM and RNN have shown superior forecasting ability than traditional machine learning models. LSTM has shown superior performance in stock market forecasting due to its ability to retain long-term memory for stock sequences (Wang et al., 2022). Petersen et al. (2019) states that, a key characteristic of an LSTM network is its ability to preserve a cell state, which carries information from earlier time steps across a sequence of inputs, such as time, while also discarding data that it seems unimportant. This makes LSTM to be able effectively to pick up relevant information from noisy data. LSTM is significantly used for time series forecasting due to its ability to capture both long-term and short-term dependencies.

In the study of Fischer & Krauss (2018), they found that LSTM based portfolio was able to create portfolio of stocks with high volatility and beta, strong short-term reversal characteristics and below-average mean momentum. According to Fischer & Krauss (2018), each of these findings is, to some degree, connected to known anomalies in capital markets. This supports the fact that LSTM is capable of extracting information from noisy as well as non-linear data.

As discussed before in this study, AI based models can capture non-linear complex patterns from data, which traditional models are not capable of. LSTM can leverage data from time series, which includes historical stock prices and financial data. LSTM process this data to identify patterns and trends for stock market forecasting (Gülmez, 2023). LSTM is particularly used for stock market forecasting due to its ability to process data with multiple input and output timesteps (Gülmez, 2023). In practice, a firm's stock value is shaped of macro-economic releases, broad market sentiment and firm specific events. LSTMs can adapt to this combination and learn the direct and indirect relationships that each factor has with price movements and then process these learned relationships into more accurate forecasts (Gülmez, 2023).

LSTM is widely used for hybrid AI models in stock market forecasting due to its inability to model future information in its predictions (Beniwal et al., 2024). Pérez-Hernández et al. (2024) presented an RNN-LMST hybrid model to better capture the volatility of market risk factors. The study showed that compared to traditional methods, RNN-LMST hybrid model has advantages in volatility forecasts which are made in market risk factors, particularly in the behaviour of volatility in stress scenarios. Moreover, the RNN-LSTM model showed superior performance in scenarios when there are large amounts of data (Pérez-Hernández et al., 2024).

As previously discussed, one of the limitations of LSTM is its inability to incorporate future information in forecasting, which restricts its capacity to fully capture complex patterns within data. According to Li et al. (2023), a key weakness of LSTM models lies in their limited ability to identify and extract meaningful features, further aggravated by representational bottlenecks that can reduce predictive accuracy. This implies that LSTM may not always be effective in filtering and processing information from different sources. Furthermore, Liao et al. (2021) emphasize that LSTMs heavily rely on long-term sequential data, which may lead to the loss of important information over extended time periods.

3.3 Empirical Evidence of AI Models in Stock Market Forecasting

Several empirical studies show that leveraging machine learning techniques can significantly improve a portfolio's risk-adjusted returns, yet the theoretical justification for the return forecasts and the investment decisions, generated by highly parameterized models are still relatively limited (Kelly et al., 2024). Kelly et al. (2024) extend recent theoretical work on highly parameterized models and shows that complexity itself can be an asset. Specifically, Kelly et al. (2024) demonstrate that market timing strategies built with ridgeless least squares estimators deliver higher out-of-sample Sharpe ratios even when the number of model parameters greatly exceeds the available sample size and only minimal regularization is used. Put differently, pushing a machine learning portfolio to be "larger than the data" can enhance performance rather than degrade it.

Furthermore, Kelly et al. (2024) state that a market-timing strategy can still generate substantial economic gains even when its out-of-sample R^2 is deeply negative. This finding suggests that researchers should place less weight on pure predictive fit metrics and instead judge models by economically meaningful criteria, such as the Sharpe ratio produced by the trading strategy they imply. Lastly, Kelly et al. (2024) put the model's theoretical predictions up against real trading data driven by machine learning rules. The empirical evidence echoes the theory: embracing higher model complexity clearly pays off. In the standard test case of forecasting the aggregate equity market and timing exposure accordingly, the resulting strategies deliver out-of-sample information ratios of about 0.3 versus a passive buy-and-hold benchmark, which is an edge that is both economically material and statistically compelling (Kelly et al., 2024).

Gu et al. (2021) in their study developed an asset pricing model, in which the factor loadings are allowed to depend on firm characteristics through a flexible, non-linear mapping. To build this mapping, Gu et al. (2021) adapted an autoencoder, an unsupervised neural network tool for dimension reduction, so that it learns not just from the return panel itself but also from the accompanying covariate data. Their latent-factor model was specifically developed to explain and predict stock returns. According to Gu et al. (2021), in the nonlinear factor framework, any return predictability attributable to firm level characteristics is transmitted only through the assets' factor loadings. In practice, the conditional autoencoder is estimated without a constant term, which hard-wires the no-arbitrage constraint into the model. This helps the model to produce more stable predictions compared to other models. Gu et al. (2021) study shows that their autoencoder asset pricing model was able to produce a higher Sharpe ratio compared to IPCA, due to its ability to generate more accurate stock market forecasts.

In the last few decades, statisticians and computer scientists have developed a host of exploratory and forecasting methods, especially in machine learning that give researchers fresh, data-driven ways to tackle asset-pricing questions (Giglio et al., 2022). When paired with traditional economic theory, these techniques allow finance scholars to test ideas more rigorously and uncover patterns that theory by itself might overlook. In turn, the empirical insights gleaned from these methods can loop back to refine and advance economic theory itself (Giglio et al., 2022). According to Giglio et al. (2022), classic econometric tools, such as cross-sectional regressions and simple portfolio sorts, struggle once the variable list grows into the dozens or hundreds, as it now has after fifty years of factor hunting. They cannot easily isolate the extra forecasting power of a new variable while simultaneously accounting for the many signals already known, nor can they protect against overfitting and multiple-testing pitfalls. Modern machine learning methods offer a way around these shortcomings (Giglio et al., 2022).

Furthermore, Giglio et al. (2022) states that machine learning approaches excel in this setting because they prioritise smart feature selection and dimensionality reduction. Machine learning trims the model's degrees of freedom and collapses overlapping information across predictors, making the forecasting task far more tractable. According to Gu et al. (2020), their research illustrates the substantial gains of incorporating machine learning when estimating expected returns. This translates into improvements in out-of-sample predictive R^2 as well as large gains for investment strategies that leverage machine learning predictions. The empirical analysis also identifies the most informative predictor variables, which helps facilitate deeper investigation into economic mechanisms of asset pricing (Gu et al., 2020).

Recent work shows that unstructured sources, such as news articles, social-media posts, and even image feeds, boost return forecasts most noticeably over very short windows (Giglio et al., 2022). The information they embed reflects shifting market sentiment rather than the slower moving fundamentals that matter over quarters or years. Because sentiment operates through subtle, nonlinear feedback loops, it is difficult to model with traditional tools (Giglio et al., 2022). Machine learning techniques, with their strength in handling high-dimensional, messy data and uncovering complex patterns, are particularly well suited to distil these signals for financial prediction (Giglio et al., 2022).

4 Limitations of AI Models in Stock Market Forecasting

Although the previous chapters have shown that AI-based models can outperform traditional methods in terms of predictive accuracy, their use is not without problems. The nature of market data, including incompleteness, temporary structural changes, and high noise levels, challenges the reliability of algorithms. In addition, complex network architectures suffer from explainability and overfitting risks and can require significant computing power and data volume. In this section, we discuss limitations of the AI models in stock market forecasting.

As AI-based forecasting models grow more difficult to understand, especially those built on DL architectures, their "black-box" nature becomes a significant risk factor (Khan et al., 2025). Limited interpretability makes it hard for investors to understand how predictions are produced, complicating efforts to assign responsibility and satisfy increasingly tighter regulatory disclosure and governance requirements (Khan et al., 2025). According to Castelvecchi (2016), the black box model is one whose internal reasoning is effectively hidden from its users. We can observe the inputs it receives and the outputs it produces, but we cannot easily trace why a particular decision was made.

A key constraint on applying AI to stock market forecasting stems from data-related issues. While AI models are efficient at storing large amounts of data, quality and readability of data can cause challenges for models (Gupta et al., 2025). Digital sources such as social media posts and online news articles are typically unstructured and may contain significant amounts of irrelevant or noisy information. Models may not be able to extrapolate sarcasm or cultural differences from the data, which may cause errors in forecasts (Gupta et al., 2025). Used data could also include misinformation or manipulation, leading models to produce inaccurate results. Issues in transparency and understanding the results of AI has led to development of Explainable Artificial Intelligence (XAI), which focuses on enhancing the transparency and interpretability of AI models (Vuković et al., 2025).

Fast development of AI has also affected regulatory frameworks. According to Vukovic et al. (2025) as AI continues to evolve rapidly, regulating its use in the financial sector has become increasingly important. While AI brings considerable benefits, such as enhanced efficiency, precision and innovation, it also introduces notable risks that demand the implementation of robust regulatory structures (Vuković et al., 2025). According to Brummer & Yadav, (2017), the FinTech sector's regulation faces a trilemma. Regulators face a trade-off between broad prohibitions ensure market safety but stifle innovation, simple frameworks encourage innovation but risk market integrity, and complex rules balance both but raise compliance costs, disproportionately affecting smaller firms.

Israel et al. (2020) studied specific hurdles that arise when using machine learning techniques for forecasting asset returns and set out a balanced view of the contexts in which these methods can genuinely add value to portfolio management. According to Israel et al. (2020), one of the limitations of AI models is overfitting. Overfitting occurs when a model becomes so flexible that it starts memorising idiosyncratic noise in the training sample instead of learning the underlying economic signal. The fit looks excellent in-sample, but because those noisy patterns do not persist, the model's predictive accuracy weakens sharply out-of-sample (Israel et al., 2020). Israel et al. (2020) state that, overfitting is most acute with highly parameterised, non-linear specifications and when researchers search exhaustively across many candidate models without suitable safeguards. Put differently, an overfitted model is too complex for the amount and stability of data available, violating the "Goldilocks" principle that the chosen specification should be neither too simple to capture real structure nor too rich to generalise.

According to Israel et al. (2020), signal-to-noise ratio is low within machine learning models. Forecasting asset returns is complicated by an unusually weak signal relative to noise. According to Israel et al. (2020), expected excess returns are small, while realised prices are dominated by unforeseen macro news and firm specific shocks. Whenever a tradable pattern does appear, competition rapidly arbitrages it away, pushing prices to levels that embed the new information and further diluting predictability. Israel et al. (2020) state that, even simple linear models often deliver in-sample R^2 values below 1 % at monthly horizons, and although predictive power rises at multi-year horizons the number of independent observations collapses. Machine learning models therefore face a delicate trade-off: they must be rich enough to capture faint signals yet sufficiently regularised to avoid over-fitting the overwhelming noise in the data. Furthermore, financial return series are intrinsically non-stationary. According to Israel et al. (2020), the statistical relationship between predictors and future prices shifts whenever market participants learn about, and trade on, a newly discovered signal. As more investors exploit the information, the mispricing is arbitraged away, so the underlying data-generating process changes in real time (Israel et al., 2020). Structural breaks can also arise from technological change, regulation, or macro-economic regime shifts. Consequently, a model that performs well today may degrade quickly tomorrow, which makes return prediction fundamentally harder than problems in domains with stable distributions. Robust asset-pricing models therefore need adaptive or online-learning components that can re-estimate parameters and detect concept drift as the market evolves (Israel et al., 2020).

According to Israel et al. (2020), in genuine big data settings, estimating a model can be computationally prohibitive. Modern machine learning practice tackles this by employing fast, approximate optimisation methods. Rather than recalculating gradients on the entire data set at every iteration, these algorithms update parameters with randomly drawn mini batches of observations (Israel et al., 2020). Using only a small sample each step greatly lowers processing time while sacrificing little, if any, estimation accuracy. Israel et al. (2020) stated that, in asset management, return forecasting the available data are limited and the predictive signals are faint. This contrasts sharply with the large, high signal data sets where ML algorithms have achieved their most spectacular successes (Israel et al., 2020). Consequently, transferring off-the-shelf, highly parameterised ML architectures to finance is far from straightforward, the information simply is not rich enough to sustain such complex models, and overfitting becomes a near certainty (Israel et al., 2020).

5 Performance of AI Models in Stock Market Forecasting

AI models have gained increasing attention in financial forecasting due to their ability to process complex and non-linear relationships in stock market data. Many researchers have shown promising results of AI models in stock market forecasting. Kara et al. (2011) in their study forecasted the movement of Istanbul Stock Exchange (ISE) between 1997 and 2007 using SVM and ANN. Both models used the same parameters and technical indicators, resulting in an average prediction performance over 75% for ANN and for SVM over 71%. According to Kara et al. (2011), both ANN and SVM showed great performance predicting stock market movements. Also, Patel et al. (2015) studied performance of SVM and ANN in CNX Nifty and S&P BSE Sensex for 10-year period between 2003-2013. AI models in this study used the same parameters and technical indicators than Kara et al. (2011) study. Patel et al. (2015) added trend deterministic data to the models, which is based on the idea that each technical indicator provides a unique perspective on stock price movement. The accuracy of the models increased over 10% after adding trend deterministic data to models. After modification, ANN was capable of forecasting index movement with over 86% accuracy and SVM with over 89% accuracy (Patel et al., 2015).

As mentioned previously in this study, traditional financial valuation models often fail to deliver accurate predictions when used with complex financial data. Furthermore, the study of Sun et al. (2019) demonstrated that non-linear models outperform traditional linear models in stock market forecasting. Sun et al. (2019) developed a hybrid model, ARMA-GARCH-NN to capture intra-day patterns for stock market shock forecasting. This approach integrates classical asset pricing frameworks with ANN models, enhanced through carefully structured feature selection and validation protocols. The model extracts market shocks using ARMA-GARCH models and predicts them by applying feature selection with ANN and ensemble learning techniques (Sun et al., 2019). The ARMA-GARCH-NN model outperformed the traditional ARMA-GARCH model due to the ARMA-GARCH model inability to capture non-linear patterns, making it impossible to capture all stock market shocks. Sun et al. (2019) also used both stock market shock prediction models in a trading strategy. ARMA-GARCH-NN was able to consistently outperform the ARMA-GARCH model in terms of cumulative return.

Although models used in Kara et al. (2011) and Patel et al. (2015) studies achieved impressive results for stock market forecasting, they have some limitations in practical application. Kara et al. (2011) stated that, choosing the right parameters for models can be hard and time consuming. Adjusting the parameters to more sensitive alternatives could also improve forecasting performance. Patel et al. (2015) also noted that SVM requires careful selection of kernel functions and tuning of parameters such as regularization making it sensitive to data characteristics and computationally intensive. ANN showed comparatively lower accuracy in this study, especially with continuous valued input data, highlighting its dependence on input representation and vulnerability to overfitting (Patel et al., 2015). These findings suggest that, while both models have strong theoretical foundations, their performance in practice is highly influenced by parameter settings and data preprocessing techniques.

Fischer & Krauss (2018) investigated LSTM forecasting abilities in S&P 500 index from 1992 until 2015. They used rules-based short-term reversal strategy, due to features they found in selected stocks. In their study, LSTM overcame every other model that they examine in the study, for example Random Forest (RAF), Deep Neural Network (DNN) and Logistic Regression (LOG). LSTM showed best performance compared to other models. LSTM had average 0.46% daily return before transaction costs, compared to RAFs 0.43%, DNNs 0.32% and LOGs 0.26%. According to Fischer & Krauss (2018), LSTM outperformed every other model due to its ability to recognize most amount of the patterns that are related to capital market anomalies and its ability to work with noisy and important data. the study also examined the models' Sharpe ratios and accuracy. LSTM showed superior performance in Sharpe ratio, reaching over 5.8. Fischer & Krauss (2018) found out in their study, that as the number of shares in the portfolio increases, LSTM's performance declined compared to other models. As the portfolio contains 200 stocks, the average daily return before transaction costs decreased to 0.1%, to the same level as RAF. Also, the Sharpe ratio decreased below RAFs (Fischer & Krauss, 2018).

Many investors are interested in long-term investment returns, rather than short-term investment returns. Beniwal et al. (2024) studied the ability of various DL models to forecast daily stock prices over long periods. Data used in study was collected from 2013 to 2023 from 5 major indices: Nifty, DJIA, DAX, NI225 and SSE. Beniwal et al. (2024) states that, LSTM performed superior compared to other models. LSTM was capable of forecasting indices price movements more accurately than other models. According to Beniwal et al. (2024) the effectiveness of LSTM in long-term stock price forecasting stems from its architecture, which is specifically designed to capture temporal dependencies in sequential data.

The performance of AI models in predicting stock market performance is measured by many different metrics and methods. Ayala et al. (2021) and Banik et al. (2022) used for example mean absolute error (MAE) and root mean squared error (RMSE) as performance metrics. Mean Absolute Error (MAE) measures the average of the absolute differences between predicted and actual values, providing an intuitive indicator of prediction accuracy without emphasizing large errors. On the other hand, Root Mean Squared Error (RMSE) measures the average magnitude of prediction errors by taking the square root of the mean of squared differences, giving greater weight to larger errors due to its quadratic nature (Banik et al., 2022). Banik et al. (2022) in their study developed system for trading that accurately forecasts future stock prices using LSTM model. The study compared performance of 10 other models such as ARIMA and Linear Regression to LSTM, and results showed superior performance of LSTM in stock market forecasting. The study concluded 3 major indices: IBEX, DAX and DJI. The LSTM model achieved RMSE value of 4.13 and MAE value of 3.24 compared to ARIMAs and Linear Regressions RMSE values of 57.41 and 7.53, and MAE values of 46.47 and 5.42 (Banik et al., 2022). Ayala et al. (2021) proposed hybrid approaches to stock market forecasting, using machine learning techniques with technical indicators. Ayala et al. (2021) noted that Linear Regression

Model and ANN performed best in their study, generating lowest values in both RMSE and MAE. Although, non-linear models have showed better performance in forecasting stock markets, Ayala et al. (2021) noted that the strong performance of the linear model may indicate that it is well-suited for short-term stock market forecasting tasks. These results highlight the superior accuracy of the LSTM model in forecasting stock prices compared to traditional models like ARIMA and Linear Regression.

Despite their strong predictive capabilities, LSTM models face several limitations in financial forecasting. According to Fischer & Krauss (2018), Banik et al. (2022) and Beniwal et al. (2024), LSTMs are sensitive to short-term reversals and microstructure noise, which may distort results. They are also prone to overfitting due to noisy, non-stationary data, and their black-box nature limits interpretability. LSTMs require significant computational resources and careful tuning, which makes its use still questionable (Fischer & Krauss 2018; Banik et al., 2022; Beniwal et al., 2024). Also, Banik et al (2022) found that LSTMs volume predictions are less reliable, which weakens overall accuracy. Furthermore, Beniwal et al. (2024) stated that LSTM processes only past data and cannot incorporate future context, which may reduce its predictive power in certain financial applications.

Bali et al. (2023) studied performance of linear and non-linear models in the U.S. stock option markets. They compared predictability of future options returns between linear and non-linear models. For linear models they used such as Ridge Regression and Lasso, and for non-linear models they used for example Random Forest and Neural Networks. The non-linear models showed better predictability for future option returns 69.8% of the months that was examined (Bali et al., 2023). Bali et al. (2023) found that non-linear models were also capable for better forecasts during the COVID-19 pandemic. This is due to non-linear models' ability to reach better predictability in other option brackets, such as those sorted by maturity and moneyness. Equity futures are also used widely for trading purposes. Bali et al. (2023) noted that non-linear long-short portfolios generated return spread of 2.04% monthly. This exceeded the linear models long-short portfolio by

0.74% per month. The result of the study shows superior performance of non-linear models in stock options forecasting.

Stock market forecasting is also widely used to build an optimal portfolio. Behera et al. (2023) constructed a hybrid model that uses ML algorithms to forecast stock returns and VaR model for portfolio selection. The portfolio is built by best performing stocks, that are forecasted by ML algorithms and evaluated using MAE and RMSE metrics. The proportion is then allocated to each best performing stock with mean-VaR model (Behera et al., 2023). The study showed promising results of AI models in portfolio optimization. Behera et al. (2023) noted that AI-based portfolios can gain better returns due to the accurate predictions of stock returns. Also, Gu et al. (2020) studied performance of 11 different ML based portfolios. Study of Gu et al. (2020) found that combining forecasts of all 11 ML models, the equally weighted portfolio reached Sharpe ratio of 2.49, which outperformed than any single model alone. Gu et al. (2020) also noted that from prior studies, Fama-French three-factor based model was able to yield 0.8 Sharpe ratio. These findings suggest that creating portfolios based on ML models can generate better risk-adjusted returns compared to traditional models.

Table 1. Summary of the Results for the Reviewed AI Models

Study (Year)	Models Evaluated	Performance
Kara et al. (2011)	ANN and SVM	ANN performed with Direc- tional accuracy of 75 %, and SVM with 71 % accuracy.
Sun et al. (2019)	ARMA-GARCH and ARMA-GARCH-NN hybrid	Higher hit-rate on intraday shock prediction and larger cumulative return in trading test
Fischer & Krauss (2018)	LSTM, Random Forest, DNN and Logistic Regression	LSTM had best daily return 0.46 % and Sharpe ratio 5.8, compared to RF daily return of 0.43% and 4.7.
Gu et al. (2020)	11 ML models and ensem- ble models	Portfolio Sharpe 2.49 com- pared to Fama-French three-factor based models 0.8
Banik et al. (2022)	LSTM, ARIMA and Linear Regression (LR)	LSTM reached RMSE (4.13) and MAE (3.24), compared to ARIMAS 57.41 and 46.47, and LRs 7.53 and 5.42.

6 Conclusion

This study examines stock market forecasting with using AI, comparing different AI models to traditional stock market forecasting models and methods. The study explores how AI-based forecasting models can overcome difficulties among the traditional methods.

Traditional stock market forecasting models are based on numerous assumptions about financial markets. Models such as CAPM, statistical- and econometric models and Fama-French Three-Factor model are based on assumptions about stationarity, linearity and investors rationality. These assumptions are frequently violated in today's complex financial markets. Also, EMH and RW are based on assumptions of investors rationality and the belief that investors are unable to forecast stock markets. However, many anomalies caused by irrational investor behaviour in markets, challenge the foundation of these theories. These anomalies create patterns, that can be detected by models, especially by AI-based models.

The findings in this study underscore that no single model universally outperforms others across all situations. The results of the models varied according to context in which they were applied. Several studies found that AI based models improve accuracy and predictability in stock market forecasting. Studies examined in this paper also found that AI based models can achieve higher Sharpe ratios due to their ability to forecast stock market movements more accurately. Many studies also highlighted the performance of hybrid models. By integrating multiple AI models together, hybrid models generated even better performance in forecasting. AI-based models can complement or even surpass traditional forecasting techniques, particularly in environments where market behaviour is non-linear, noisy and rapidly changing. Techniques like deep learning, while more resource intensive, hold promise for real time decision-making. The findings of this paper suggest that using AI-based models in stock market forecasting can enhance investors decision-making to make more profitable investments in stock market.

However, despite their potential, AI models present several challenges. High computational costs, lack of interpretability and the "black box" nature of DL models pose obstacles to broader adoption. Financial decision-making often requires transparency and explainability, both for regulatory compliance and for maintaining stakeholder confidence. Future research should therefore emphasize the development of hybrid models that combine the flexibility and accuracy of AI with the interpretability of traditional finance theories.

Future research should expand the evaluation of AI-based forecasting models by incorporating advanced sequence models. Comparative studies across different market conditions and asset classes such as cryptocurrencies and commodities would also provide valuable insights into the generalizability and robustness of these models. Future work should focus on improving model interpretability and developing hybrid approaches that combine the accuracy of AI with the transparency required in financial decision-making.

This thesis concludes that AI is not just a supplementary tool, but a critical component in the evolution of modern financial forecasting and portfolio management. While traditional methods will continue to serve foundational roles, AI offers powerful enhancements, particularly under uncertain market conditions. As the field evolves, the combination of ML techniques, real-time data and domain expertise will define the next generation of financial decision-making tools, tools that are not only more adaptive and precise, but also more aligned with the realities of today’s financial markets.

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