

Chapter 2: Background and Related Work

2.1 Introduction

This chapter presents the theoretical background and related work in the area of stock market prediction using AI. It reviews the theories of fundamental and technical analysis as well as the various models of machine learning. Furthermore, it also presents relevant studies conducted in various countries, including Saudi Arabia, to identify the existing gaps in the literature.

2.2 Stock Market Forecasting

Stock market forecasting is a process of determining the future price movement of stocks based on available information from past movements. Stock markets are characterized by non-linear and non-stationary time series data due to the variety of factors influencing stock prices. Moreover, the challenges of stock market forecasting are more pronounced in emerging markets like the Saudi Stock Market.

2.3 Fundamental Analysis

Fundamental analysis evaluates the intrinsic value of a company by analyzing its financial data, such as financial ratios. Commonly used financial ratios include:

- Price-to-earnings (P/E) ratio
- Return on equity (ROE)
- Debt-to-equity (D/E) ratio

This approach has been proven to be successful in determining the long-term value of stocks. However, it is not effective in providing traders with information regarding the short-term movements of stock prices.

2.4 Technical Analysis

Contrary to fundamental analysis, technical analysis determines the future price of stocks by studying past price and volume movements.

Various technical indicators are used, including the relative strength index (RSI), moving averages, MACD indicators, and Bollinger bands.

Technical analysis is useful for short-term movements but does not account for the financial strength of the company.

2.5 Machine Learning in Finance

Machine learning models can identify non-linear relationships in large data sets.

Various models have been applied, including Random Forest, support vector machines (SVM), and gradient boosting models.

Deep learning models such as long short-term memory (LSTM) networks have shown potential for stock market analysis. However, the majority of models rely solely on price data.

2.6 Hybrid Integration of Technical and Fundamental Analysis

In many cases, it is more beneficial to use a variety of data sources or models within an approach than to rely upon only one. In the realm of stock market and stock price prediction, it may be beneficial to use a variety of different data sources to provide for more comprehensive and accurate predictions. For instance, technical indicators may reflect the technical strength of the stocks listed on the exchanges, while fundamental indicators may reflect the financial strength of those listed companies.

The approach to be used within this project utilizes two different models. The first model to be utilized is a Bidirectional Long Short-Term Memory (BiLSTM) model, which will help to recognize and account for technical features within the market. An XGBoost model will help to recognize and account for both technical and fundamental features of the stocks. Rather than providing a prediction of the price of the stock, the two models will provide an estimate of the probability of succeeding in the trade.

The probability of succeeding in a trade is determined by creating a weighted average of the two models’ predictions. The resulting probability can then be compared against predetermined thresholds that indicate whether or not a trading signal should be created based upon those models’ results. By utilizing both technical and fundamental data in the trading signal generation process, the framework can be beneficial in improving the quality of those trading decisions..

Comparison of Stock Market Prediction Approaches			
Technical Analysis vs Fundamental Analysis vs Hybrid Approach			
Aspect	Technical Analysis	Fundamental Analysis	Hybrid Model (Proposed)
Data Type	Price & Volume (High-frequency)	Financial Statements (Low-frequency)	Both Price Data & Financials
Time Horizon	Short-term (Days/Weeks)	Long-term (Months/Years)	Short to Medium-term
Key Indicators	RSI, MACD, MA, Bollinger Bands	P/E, ROE, D/E, Cash Flow	Combined Technical & Fundamental
Strengths	Market timing, Entry/Exit signals	Company valuation, Intrinsic value	Timing + Valuation
Weaknesses	Ignores company health, False signals	Ignores market sentiment, Lagging data	Complex integration, Model overfitting

Source: Academic Research 2024

Figure 2.1: Comparison of Technical, Fundamental, and Hybrid Approaches

2.7 Trading-Oriented Evaluation Metrics

Most of the existing studies on stock market prediction using machine learning methodologies focus mainly on classification metrics in statistics. However, despite their usefulness, such metrics do not provide a complete evaluation of the economic value of a trading model.

In addition to classification metrics, trading-oriented metrics must also be considered to evaluate the performance of a trading model. Metrics such as total

return, win rate, Sharpe ratio, and maximum drawdown can provide valuable insights into the trading model's profitability and risk.

For the defined problem, the target variable represents the stock's price movement, with a successful trade occurring when the price reaches a take-profit level of +5% before reaching a stop-loss level of -2%, as observed in the subsequent price movement of the stock.

2.8 Evolution of Financial Prediction Models

Financial market theories began with the Efficient Market Hypothesis, which suggested that stock market prices reflect all available information and that it is therefore difficult for investors to make accurate price predictions (Fama, 1970). However, models like ARIMA (AutoRegressive Integrated Moving Average) were developed that could help forecast stock prices and other financial time-series indicators (Adebiyi et al., 2014).

Stock market data are complex and often nonlinear in their relationships. Thus, traditional statistical models may not be able to accurately describe the complex relationships within the markets. Consequently, alternative machine learning models that can learn nonlinear relationships within the market data are often employed as prediction models.

Deep learning models have been particularly useful for recognizing the complex temporal relationships between stock market data. For instance, LSTM (Long Short-Term Memory) models have been used for stock market prediction due to their ability to identify patterns in data that are sequenced over time (Hochreiter & Schmidhuber, 1997; Fischer & Krauss, 2018). Additionally, models like XGBoost have also been used for stock market prediction, indicating their strong performance in tasks utilizing structured data tables (Chen & Guestrin, 2016).

2.9 Machine Learning and Deep Learning Studies

Machine learning and deep learning algorithms have been applied to the task of stock market prediction. For instance, one study that examined various machine learning methods for forecasting stock market indicators found that different models performed better than others depending on the specific considerations of

that stock market and its movements (Ahmed et al., 2010). Additionally, models like random forests and gradient boosting methods have been applied to financial markets prediction studies due to their success in recognizing complex nonlinear relationships within data (Breiman, 2001; Chen & Guestrin, 2016).

Deep learning models, such as those that utilize stacked autoencoders and LSTMs, have been proposed for studying financial time-series data (Bao et al., 2017). For example, both Fischer and Krauss (2018) and Krauss et al. (2017) have published studies that explore the use of LSTM models for stock market prediction, as well as the comparison of deep learning models for statistical arbitrage.

In addition, deep learning models based on language models, such as the Informer model, have also been proposed to improve the prediction of long sequences of time-series data in financial markets (Zhou et al., 2021).

As with many AI models for stock market prediction, the majority of existing research utilizes indicators of price movements to attempt to classify whether stock prices will rise or fall. However, few current studies have attempted to evaluate whether those price predictions can be used to create profitable trading strategies for investors.

2.10 Hybrid Models in Literature

Hybrid approaches have increasingly gained attention in stock market prediction research due to their ability to combine the strengths of multiple data sources and predictive models. Earlier studies demonstrated that combining forecasting techniques often leads to superior predictive performance compared with relying on a single model. Tsai and Wang (2009) showed that hybrid machine learning frameworks can improve prediction accuracy by leveraging complementary modeling capabilities.

Nti et al. (2020) conducted a comprehensive review of stock market prediction studies and categorized them into technical, fundamental, and combined approaches. Their findings revealed that relatively few studies integrate both technical and fundamental information, despite the potential advantages of combining these complementary sources of information.

Daradkeh (2022) proposed a hybrid CNN-BiLSTM framework enhanced with sentiment analysis for stock market forecasting. The study demonstrated that combining financial indicators with additional information sources can improve predictive performance. However, reliance on sentiment and news data may introduce noise, increase data complexity, and reduce reproducibility.

Ansari et al. (2024) introduced a reinforcement learning framework that integrated technical indicators and fundamental variables within a risk-aware trading environment. Their results suggested that combining multiple categories of financial information can improve trading outcomes. Nevertheless, reinforcement learning systems often suffer from limited interpretability and require extensive tuning and validation.

More recently, Din et al. (2025) developed an attention-customized BiLSTM and XGBoost ensemble model for financial prediction. Their study demonstrated that integrating deep learning architectures with gradient boosting techniques can improve predictive capability by combining temporal pattern recognition with structured feature learning. However, the study primarily focused on prediction performance rather than risk-adjusted trading evaluation.

Overall, existing hybrid studies indicate that combining multiple models and information sources can improve forecasting performance. Nevertheless, most existing research remains focused on prediction accuracy rather than evaluating whether those predictions translate into profitable and risk-controlled trading decisions. This limitation motivates the development of the present study.

2.11 Studies in Emerging and Saudi Markets

Artificial intelligence applications in stock market prediction have attracted growing interest in emerging financial markets, where market structures, liquidity conditions, and investor behavior often differ from those of developed economies. These characteristics create opportunities for developing specialized prediction frameworks tailored to local market conditions.

Within the Saudi Stock Market (Tadawul), several studies have explored the use of machine learning and deep learning techniques. Al-Nefaie and Aldhyani (2022) applied LSTM and multilayer perceptron models to forecast adjusted closing prices across multiple Saudi market sectors. Their findings demonstrated the effectiveness of deep learning models in capturing temporal market patterns.

However, their work focused primarily on price forecasting rather than trading outcome prediction.

Alsulmi and Al-Shahrani (2022) proposed a machine-learning-based trading framework for Tadawul. While their study incorporated elements of trading decision support and risk management, it did not integrate company-level fundamental indicators into the prediction process.

Khurayshi and Alharbi (2025) compared several machine learning algorithms, including Linear Regression, Random Forest, XGBoost, and AdaBoost, for Saudi stock price prediction. Their results contributed valuable evidence regarding the effectiveness of machine learning models in the Saudi market. However, the study focused on next-day price forecasting and did not evaluate risk-adjusted trading performance.

Additional recent studies have further expanded the application of machine learning within Saudi financial markets. Forecasting of Saudi Stock Prices Using Statistical and Machine Learning Models (2025) compared traditional statistical methods with machine learning approaches and demonstrated the growing effectiveness of advanced predictive techniques for Saudi stocks. Nevertheless, the primary emphasis remained on forecasting accuracy rather than trading profitability.

Recent review studies have also highlighted the increasing role of artificial intelligence in financial forecasting. Deep Learning for Financial Forecasting: A Review of Recent Advances (2025) and Artificial Intelligence in Financial Market Prediction (2025) emphasized the growing adoption of hybrid models, ensemble learning methods, and risk-aware evaluation frameworks in financial applications.

Despite these advances, relatively few studies within the Saudi market combine technical indicators, company-level fundamental ratios, hybrid machine learning architectures, and risk-adjusted trading evaluation metrics within a unified framework. This limitation forms an important motivation for the present study.

2.12 Research Gap and Study Positioning

The review of existing literature reveals several important research gaps.

First, many studies continue to examine technical analysis and fundamental analysis independently. Technical indicators are effective for capturing short-term market dynamics but provide limited insight into the underlying financial quality of firms. Conversely, fundamental indicators reflect company strength and valuation but often fail to capture short-term market movements. Relatively few studies integrate both perspectives within a unified prediction framework.

Second, the majority of existing research focuses on forecasting stock prices, market trends, or directional movements. While prediction accuracy is frequently reported, limited attention has been given to determining whether those predictions lead to profitable trading outcomes under realistic trading conditions.

Third, most studies evaluate model performance using statistical metrics such as accuracy, precision, recall, F1-score, and AUC. Comparatively few studies employ risk-adjusted financial performance measures such as Sharpe Ratio, Maximum Drawdown, Win Rate, and Total Return when assessing the practical value of prediction models.

Fourth, existing studies rarely formulate the prediction task as a trading outcome classification problem based on explicit take-profit and stop-loss rules. Most research predicts future prices directly without evaluating whether a trading opportunity ultimately succeeds or fails.

Finally, although research on artificial intelligence in the Saudi Stock Market has expanded in recent years, there remains a limited number of studies that simultaneously combine technical indicators, fundamental financial ratios, hybrid machine learning models, and risk-adjusted trading evaluation within the Tadawul market.

To address these gaps, the present study proposes a hybrid framework that integrates XGBoost and BiLSTM models using both technical indicators and fundamental financial ratios. Rather than forecasting future prices, the framework predicts trading outcomes based on predefined take-profit and stop-loss levels and evaluates performance using both classification metrics and risk-adjusted trading measures.

Study	Technical	Fundamenta	Hybrid AI Model	Trading Outcome	TP/SL Logic	Risk-Adjusted Metrics	Saudi Market
Nti et al. (2020)	✓	✓	✓	✗	✗	✗	✗
Daradkeh (2022)	✓	Partial	✓	✗	✗	✗	✗
Al-Nefaie & Aldhyani (2022)	✓	✗	✗	✗	✗	✗	✓
Alsulmi & Al-Shahrani (2022)	✓	Partial	✗	Partial	✗	Partial	✓
Ansari et al. (2024)	✓	✓	✓	Partial	✗	Partial	✗
Khurayshi & Alharbi (2025)	✓	✗	✗	✗	✗	✗	✓
Forecasting Saudi Stock Prices (2025)	✓	✗	✗	✗	✗	✗	✓
Din et al. (2025)	✓	✓	✓	✗	✗	✗	✗
Present Study	✓	✓	✓	✓	✓	✓	✓

Table 2.2 highlights the distinguishing characteristics of the reviewed studies relative to the present research. While several studies employed technical indicators, fundamental variables, or hybrid machine learning architectures, few integrated all of these components within a single framework. Furthermore, most existing studies focused primarily on stock price prediction and conventional classification performance metrics. In contrast, the present study combines technical indicators and fundamental financial ratios within a hybrid BiLSTM–XGBoost architecture, formulates the prediction task using explicit take-profit and stop-loss trading rules, and evaluates performance using risk-adjusted trading metrics such as Sharpe Ratio and Maximum Drawdown. This combination of features distinguishes the proposed framework from previous studies, particularly within the context of the Saudi Stock Market (Tadawul).

Figure 2.2: Research Gap and Hybrid Model

Table 2.1 – Comparative Summary of Related Studies and Research Gap

Author(s)	Market / Context	Data Type	Model / Method	Key Contribution	Limitation / Research Gap
Nti et al. (2020)	Global Stock Markets	Technical, Fundamental, and Combined Analysis Studies	Systematic Literature Review	Categorized stock prediction studies into technical, fundamental, and combined	Focuses on literature synthesis rather than proposing a practical prediction or

				approaches and highlighted the limited use of integrated frameworks.	trading framework.
Daradkeh (2022)	Dubai Financial Market	Financial Indicators, News Events, and Sentiment Data	CNN-BiLSTM Hybrid Framework	Demonstrated that combining sentiment information with market data improves prediction performance.	Heavy dependence on sentiment and news data may introduce noise and reduce reproducibility.
Al-Nefaie and Aldhyani (2022)	Saudi Stock Exchange (Tadawul)	Historical Stock Price Data	LSTM and MLP Models	Applied deep learning techniques to forecast stock closing prices across multiple Saudi market sectors.	Focused on price forecasting rather than trading outcome prediction or risk-adjusted evaluation.
Alsulmi and Al-Shahrani (2022)	Saudi Stock Exchange (Tadawul)	Market Data and Trading Actions	Machine Learning-Based Automated Trading Framework	Developed a machine learning trading framework incorporating automated decision-making and risk management concepts.	Did not integrate fundamental financial ratios or compare hybrid technical-fundamental architectures.
Ansari et al. (2024)	Dow Jones Multi-Stock Market	Technical Indicators and Fundamental Variables	Reinforcement Learning (A2C and DDPG)	Demonstrated that combining technical and fundamental information can improve trading performance.	Reinforcement learning models are difficult to interpret and require extensive tuning and validation.
Khurayshi and Alharbi (2025)	Saudi Stock Market	Historical Market Data	Linear Regression, Random Forest,	Compared several machine learning	Concentrated on next-day price prediction and accuracy metrics

			XGBoost, and AdaBoost	models for stock prediction within the Saudi market.	rather than trading profitability and risk control.
Forecasting of Saudi Stock Prices Using Statistical and Machine Learning Models (2025)	Saudi Stock Exchange (Tadawul)	Historical Stock Price Data	ARIMA, LSTM, Random Forest, XGBoost, SVR, KNN, and Decision Tree	Conducted a comprehensive comparison of statistical and machine learning methods for Saudi stock forecasting.	Focused primarily on forecasting accuracy rather than evaluating practical trading outcomes.
Din et al. (2025)	Bitcoin	Sequential Financial Data and Structured Features	Attention-Customized BiLSTM and XGBoost Ensemble	Demonstrated the effectiveness of combining BiLSTM and XGBoost within an ensemble framework.	Focused on predictive performance and did not explicitly evaluate trading strategies using risk-adjusted metrics.
Deep Learning for Financial Forecasting: A Review of Recent Advances (2025)	Global Financial Markets	Multiple Financial Datasets	Review Study	Summarized recent advances in deep learning applications for financial forecasting and highlighted emerging hybrid architectures.	Review study only; does not provide a practical Saudi-specific implementation.
Artificial Intelligence in Financial Market Prediction (2025)	Global Financial Markets	Multiple Financial Datasets	Review Study	Examined the evolution of AI-based prediction models and identified future research directions.	Broad review without implementation of a trading-oriented prediction framework.
Saberironaghi et al. (2025)	Global Financial Markets	Multiple Financial Datasets	Review of Machine Learning and	Reviewed predictive models,	Does not propose a Saudi-specific framework or

			Deep Learning Models	datasets, evaluation metrics, and challenges in stock market forecasting research.	incorporate explicit trading constraints.
Present Study	Saudi Stock Market (Tadawul)	Daily Market Data and Annual Financial Ratios	XGBoost, BiLSTM, and Weighted Hybrid Ensemble	Integrates technical indicators and fundamental financial ratios within a hybrid framework using explicit take-profit and stop-loss trading logic and evaluates performance using risk-adjusted trading metrics.	Limited to 20 Tadawul companies and simplified backtesting assumptions.

Table 2.1 – Comparative Summary of Related Studies and Research Gap

Table 2.1 presents a summary of key studies related to stock market prediction, hybrid artificial intelligence models, financial forecasting, and the application of machine learning techniques within emerging and Saudi financial markets. The reviewed studies include empirical investigations, hybrid prediction frameworks, and recent review articles that collectively provide a comprehensive understanding of the evolution of AI-based financial forecasting.

As illustrated in Table 2.1, researchers have employed a wide range of approaches, including machine learning, deep learning, ensemble learning, reinforcement learning, and hybrid architectures. Several studies demonstrated the benefits of combining multiple data sources and predictive techniques to improve forecasting performance. However, important limitations remain. Many existing studies focus primarily on stock price forecasting and conventional classification accuracy measures, while relatively few evaluate the practical trading value of their predictions through risk-adjusted financial metrics. In addition, several studies either rely exclusively on technical indicators or focus solely on fundamental

information, limiting their ability to capture both market dynamics and firm-level financial strength simultaneously.

Although recent research has expanded the application of artificial intelligence within the Saudi Stock Market (Tadawul), relatively few studies have integrated technical indicators, fundamental financial ratios, hybrid machine learning architectures, and risk-adjusted trading evaluation within a single framework. Furthermore, limited attention has been given to formulating stock prediction as a trading outcome classification problem based on explicit take-profit and stop-loss rules.

The present study addresses these limitations by proposing a weighted hybrid framework that combines XGBoost and BiLSTM models using both technical indicators and fundamental financial ratios. Unlike many previous studies that focus on stock price forecasting, the proposed framework predicts trading outcomes and evaluates performance using both classification metrics and risk-adjusted trading measures, including Sharpe Ratio, Maximum Drawdown, Win Rate, and Total Return.

2.13 Comparative Analysis with Existing Studies

The studies reviewed in Table 2.1 demonstrate the growing application of artificial intelligence techniques in stock market forecasting and financial decision-making. Researchers have employed a variety of approaches, including machine learning, deep learning, ensemble learning, reinforcement learning, and hybrid architectures. These studies have contributed significantly to improving forecasting accuracy and understanding market behavior.

Despite these contributions, several limitations remain. A large proportion of existing studies focus primarily on forecasting stock prices, directional movements, or classification accuracy. Other studies rely on sentiment analysis, news data, or social media information to enhance prediction performance. While these approaches may improve predictive capability, they often provide limited insight into whether the resulting predictions translate into profitable and risk-controlled trading decisions.

The present study differs from the existing literature by integrating technical indicators and fundamental financial ratios within a weighted hybrid framework based on XGBoost and BiLSTM models. Furthermore, rather than forecasting

future stock prices directly, the proposed framework formulates the problem as a trading outcome classification task based on predefined take-profit and stop-loss rules.

Another distinguishing feature of the present study is its emphasis on practical trading evaluation. In addition to traditional classification metrics, the proposed framework evaluates performance using financial measures such as Total Return, Win Rate, Sharpe Ratio, and Maximum Drawdown. Consequently, the study extends beyond prediction accuracy and focuses on the economic value and risk-adjusted performance of AI-generated trading signals.

2.14 Positioning of the Present Study

The present study contributes to the growing body of literature on artificial intelligence applications in financial markets by proposing a hybrid framework specifically designed for trading signal generation in the Saudi Stock Market (Tadawul). The framework combines technical indicators and fundamental financial ratios within two complementary machine learning models: XGBoost and Bidirectional Long Short-Term Memory (BiLSTM).

Unlike many existing studies that focus primarily on forecasting stock prices or market direction, this research formulates the prediction task as a classification problem that estimates the probability of a stock reaching a predefined take-profit level before reaching a stop-loss level. This formulation aligns the prediction process more closely with practical trading decision-making.

The proposed framework also extends existing literature through its evaluation methodology. Rather than relying exclusively on statistical prediction metrics, the study incorporates risk-adjusted trading measures, including Sharpe Ratio, Maximum Drawdown, Win Rate, and Total Return. This approach enables a more comprehensive assessment of the practical value of AI-generated trading signals.

Accordingly, the present study occupies a distinct position within the literature by integrating technical and fundamental analysis, hybrid machine learning architecture, explicit trading constraints, and risk-adjusted performance evaluation within the context of the Saudi Stock Market.

2.15 Chapter Summary

This chapter reviewed the theoretical foundations and related literature concerning stock market forecasting, technical analysis, fundamental analysis, machine learning, deep learning, hybrid artificial intelligence models, and studies conducted within emerging and Saudi financial markets.

The literature demonstrates that artificial intelligence techniques have become increasingly important in financial forecasting. However, most existing studies focus primarily on stock price prediction and conventional classification performance measures. Relatively few studies evaluate whether such predictions result in profitable and risk-controlled trading outcomes. Furthermore, many studies rely exclusively on either technical indicators or fundamental information, while only a limited number attempt to integrate both sources of information within a unified framework.

The review also revealed that research dedicated specifically to the Saudi Stock Market remains relatively limited, particularly studies that combine technical indicators, fundamental financial ratios, hybrid machine learning models, and risk-adjusted trading evaluation metrics. These limitations highlight a clear research gap within the current literature.

To address this gap, the present study proposes a hybrid XGBoost–BiLSTM framework that integrates technical and fundamental analysis and evaluates trading outcomes using both classification metrics and risk-adjusted financial performance measures. The next chapter presents the methodology adopted to develop, train, and evaluate the proposed framework.