The use of Extreme Gradient Boosting in predicting stock prices of selected companies in the Iraqi Stock Exchange

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Received: 14.07.2024 Revised: 22.08.2024 Accepted: 25.09.2024

ABSTRACT
This paper analyzes stock price data from 20 companies listed on the Iraqi Securities Exchange over the period from early 2020 to late 2023, employing the Extreme Gradient Boosting algorithm to uncover optimal adjustable parameters and evaluation metrics for various stock symbols. Key parameters such as Max Depth, Gamma, Learning Rate, and N Estimators are examined to understand their influence on model complexity and prediction accuracy. The findings illustrate that a max depth of 12 or 18 provides a balance between capturing complex relationships and avoiding overfitting, with companies exhibiting varying depths corresponding to their unique performance drivers. Gamma values highlight the trade-off between model complexity and interpretability, where lower values allow for intricate relationships while higher values promote simplicity. Learning rates around 0.05 indicate stability in convergence, while varying N Estimators (400 vs. 500) affect model performance and training efficiency. The evaluation metrics, including MSE, RMSE, MAE, MAPE, and R^2, provide insights into the effectiveness of the models, with companies like Mosul Bank demonstrating low error metrics and strong predictive capabilities. Overall, the study emphasizes the importance of parameter selection and evaluation metrics in enhancing the prediction accuracy of stock price dynamics in the Iraqi market, offering valuable insights for investors and stakeholders.

Keywords: Stock Price Prediction, Extreme Gradient Boosting, Iraqi Securities Exchange, Model Evaluation Metrics.

1. INTRODUCTION

The prediction of stock prices has emerged as a central theme in financial research, providing essential insights that guide investors and corporate decision-makers. Accurate forecasting of stock prices not only aids in achieving better financial outcomes but also enhances the efficiency of financial markets. Among various forecasting techniques, machine learning models have gained prominence due to their ability to analyze large datasets and capture complex patterns in financial time series data (Zhang & Xu, 2019). This paper focuses on the application of Extreme Gradient Boosting for predicting stock prices within the Iraq Stock Exchange (ISX), an important but under-researched venue in the context of emerging markets.

The ISX serves as a critical hub for investment in Iraq, reflecting the country's economic conditions, political stability, and market sentiments. Challenges such as market inefficiency, limited liquidity, and external economic influences frequently impact stock prices in Iraq (Otto et al., 2020). Additionally, the Iraqi financial market exhibits high volatility, exacerbated by geopolitical factors and fluctuating oil prices, which are vital for the country's economy (Al-Okaily, 2021). Consequently, the demand for effective predictive models becomes evident, particularly as investors seek to navigate these complexities.

Extreme Gradient Boosting is recognized for its superior performance in classification and regression tasks, making it an attractive option for stock price prediction (Chen & Guestrin, 2016). It operates by constructing an ensemble of decision trees, optimizing performance through gradient boosting techniques. Compared to traditional methods such as linear regression or time series analysis, Extreme

Gradient Boosting capturesnon-linear relationships and interactions among variables, which are common in stock price dynamics (He & Bai, 2020). Moreover, its flexibility allows for the inclusion of a diverse range of features, such as historical prices, trading volumes, and various macroeconomic indicators, rendering it a robust choice for predictive modeling in the volatile context of the ISX (Jiang et al., 2020).
This research aims to evaluate the effectiveness of Extreme Gradient Boosting in predicting stock prices within the Iraqi market while addressing the unique challenges posed by its economic and political landscape. By doing so, this study contributes to the broader literature on stock price prediction in emerging markets, offering insights that can benefit investors, policymakers, and academics alike. The integration of machine learning techniques with financial theories presents an opportunity to improve predictive accuracy and inform investment strategies in the context of developing economies.
To effectively apply Extreme Gradient Boosting for stock price prediction in the Iraq Stock Exchange, a rigorous methodology must be employed that encompasses data collection, preprocessing, model training, validation, and evaluation. The initial step involves the accumulation of relevant data, which should include historical stock prices, trading volumes, and macroeconomic indicators such as exchange rates, inflation rates, and oil prices. Data can be sourced from various platforms, such as financial news websites and official ISX reports, ensuring a comprehensive dataset for analysis (Al-Masum & Abdulkareem, 2020).
Once the data is collected, the preprocessing phase is critical. This stage involves cleaning the data by handling missing values, removing duplicates, and normalizing the features to ensure that they are on a comparable scale. Feature engineering can also enhance predictive performance by creating additional informative variables from existing data, such as moving averages or technical indicators (Yazdani et al., 2021).
The next phase involves splitting the dataset into training and testing subsets to evaluate the performance of the Extreme Gradient Boosting model accurately. The training set is used for model fitting, where Extreme Gradient Boosting 's hyperparameters, such as learning rate, max depth, and number of estimators, can be optimized using techniques such as cross-validation. This process allows the model to learn from the data and identify patterns that could indicate future stock movements (Caruana & Niculescu-Mizil, 2006).
Once trained, the model's performance on the testing set can be measured using various metrics such as Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and R-squared (R^2) values. These metrics provide insight into the model’s ability to generalize to unseen data and assess its predictive accuracy (Khan et al., 2020). Additionally, it is vital to analyze feature importance to understand which factors significantly contribute to price movement. Extreme Gradient Boosting provides intrinsic capability to evaluate feature importance, which aids in making informed investment decisions based on driving factors rather than mere predictions.
The importance of employing Extreme Gradient Boosting in stock price prediction, particularly in an emerging market like Iraq, cannot be overstated. Traditional econometric models may be less effective in capturing the complexities of stock price movements in such a volatile environment. In contrast, machine learning approaches, specifically Extreme Gradient Boosting, offer a higher degree of flexibility and adaptability to non-linear relationships and interactions between variables (Khamis & Omer, 2020). Furthermore, as the financial landscape evolves, machine learning methods can continually learn and adapt, improving the accuracy and performance of predictions over time.
This paper presents a novel method for predicting stock prices by utilizing the Extreme Gradient Boosting predictor alongside instantaneous components derived from stock price data, employing various types of binary gray wolf optimizers. The analysis is based on stock price data from 20 selected companies listed on the Iraq Securities Exchange, covering the period from early 2020 to the end of 2023. The subsequent sections provide a detailed discussion of the proposed approach. The second section reviews the theoretical framework and relevant empirical studies from recent years. The third section outlines the research methodology. The findings are presented in the fourth section, followed by the conclusion in the fifth section.

2. REVIEW OF LITERATURE

Stock price prediction has become a significant research area due to its implications for investors, financial analysts, and policymakers. Accurate predictions can lead to informed decision-making, improved investment strategies, and enhanced market efficiency. The introduction of machine learning methods has transformed this field, offering advanced tools capable of capturing complex patterns in financial data. Among these methods, Extreme Gradient Boosting has gained notable attention due to its high performance in various prediction tasks (Chen & Guestrin, 2016).

The Iraq Stock Exchange (ISX) presents a unique landscape for stock price prediction. As a developing market, the ISX is influenced by various factors, including political instability, economic uncertainty, oil price fluctuations, and foreign investments (Al-Mamory et al., 2020). These characteristics create challenges for traditional forecasting methods, which may struggle to account for the volatility and complexities inherent in such an environment. Thus, machine learning approaches, particularly Extreme Gradient Boosting, can offer more robust solutions, adapting to the changing dynamics of the market (Abdul-Maksoud et al., 2021).
The objective of this literature review is to explore the application of Extreme Gradient Boosting in predicting stock prices in the ISX by analyzing existing research, methodologies, and findings. This review will highlight the advantages of using Extreme Gradient Boosting over traditional econometric models and assess its performance in the context of the Iraqi market. Additionally, it will evaluate the potential challenges and limitations of employing Extreme Gradient Boosting in this setting.

2.1 Overview of Extreme Gradient Boosting

Extreme Gradient Boosting is an implementation of gradient boosted decision trees designed for speed and performance (Chen & Guestrin, 2016). Unlike traditional boosting methods, Extreme Gradient Boosting optimizes the computational efficiency and memory usage, allowing it to handle large datasets easily. The architecture of Extreme Gradient Boosting provides advantages such as parallel processing and tree pruning, contributing to its popularity in machine learning competitions and applications in numerous domains, including finance (Caruana & Niculescu-Mizil, 2006).
Extreme Gradient Boosting 's effectiveness in stock price prediction stems from its ensemble learning approach. By combining the predictions of multiple weak learners (decision trees), Extreme Gradient Boosting can capture complex relationships and interactions among independent variables (He & Bai, 2020). This capability is particularly valuable in financial data, where non-linear relationships are commonplace. Additionally, Extreme Gradient Boosting includes regularization to prevent overfitting, which is crucial given the limited size of datasets typically available in emerging markets like Iraq (Al-Okaily, 2021).
Several recent studies have demonstrated Extreme Gradient Boosting 's superiority over traditional models. For example, Yazdani et al. (2021) conducted a comparative analysis and found that Extreme Gradient Boosting consistently yielded better accuracy than traditional time series models such as ARIMA. This finding aligns with the significant interest in applying machine learning techniques in areas like financial forecasting, particularly in emerging markets that exhibit different behaviors than more developed markets (Jiang et al., 2020).

2.2 Application of Extreme Gradient Boosting in Emerging Markets

Emerging markets like Iraq present unique challenges and opportunities for stock price prediction. Economic instability, lower liquidity, and limited access to historical financial data can complicate predictive modeling. However, they also provide an essential testbed for innovative approaches like Extreme Gradient Boosting, which has shown promise in handling the complexities of such markets (Khamis & Omer, 2020).
Research conducted on the ISX indicates that machine learning techniques outperform traditional econometric models. For instance, Al-Mamory et al. (2020) analyzed the volatility of stock prices in the ISX and found that incorporating machine learning models significantly improved predictive performance. Their results suggest that methods like Extreme Gradient Boosting could enhance the investment strategies of both local and foreign investors by providing actionable insights into price movements.
Furthermore, the non-linear nature of stock price movements in the ISX necessitates modeling techniques capable of adapting to rapidly changing environments. Abdul-Maksoud et al. (2021) employed Extreme Gradient Boosting to predict stock prices in the ISX, emphasizing its ability to analyze historical price data alongside contextual economic indicators. Their findings confirmed that the inclusion of additional features, such as macroeconomic variables and trading volumes, significantly improved predictive outcomes.
Despite these advancements, challenges remain. Many studies highlight issues such as data scarcity, market inefficiencies, and the need for continuous model adaptation to changes in the political and economic landscape of Iraq (Otto et al., 2020). Therefore, while Extreme Gradient Boosting presents a promising approach, it must be complemented by robust data collection and market analysis strategies.

2.3 Methodological Insights in Existing Literature

The methodological framework for employing Extreme Gradient Boosting in stock price prediction typically involves several key steps: data collection, preprocessing, feature engineering, model training,

and evaluation. Most studies emphasize the importance of curating a comprehensive dataset that includes both historical stock prices and relevant macroeconomic indicators such as inflation rates, exchange rates, and oil prices (Yazdani et al., 2021).
Feature engineering plays a pivotal role in improving model accuracy. Researchers have utilized various techniques to extract meaningful features from raw data, including the calculation of moving averages, trading volume changes, and technical indicators like Relative Strength Index (RSI) and Moving Average Convergence Divergence (MACD). These features can provide additional context for the model, allowing it to capture potential turning points in stock price trends (Chen et al., 2019).
Moreover, the iterative process of hyperparameter tuning is crucial for optimizing Extreme Gradient Boosting 's performance. Studies have shown that employing techniques like grid search and randomized search can lead to improved model outcomes (Khan et al., 2020). These processes enable researchers to identify the best combinations of parameters, enhancing predictive accuracy in the volatile context of the ISX.
Importantly, model evaluation metrics such as Mean Absolute Error (MAE) and Root Mean Square Error (RMSE) are commonly used to assess the performance of Extreme Gradient Boosting in stock price predictions. Positive outcomes in evaluations reinforce the argument for integrating machine learning approaches into financial forecasting, particularly in emerging markets where economic variables can shift quickly (Caruana & Niculescu-Mizil, 2006).

2.4 Review of Empirical Studies
Yazdani et al. (2021) conducted a comprehensive study comparing various machine learning algorithms for stock price prediction. They examined models including Extreme Gradient Boosting, Random Forest, and LSTM (Long Short-Term Memory). Their findings indicated that Extreme Gradient Boosting achieved the highest accuracy in forecasting stock prices due to its ability to handle large datasets and non-linear relationships effectively. They emphasized feature selection's importance in enhancing model performance and suggested further research into hybrid models that combine different approaches for improved accuracy.
Abdul-Maksoud et al. (2021) implemented machine learning techniques on the Iraq Stock Exchange (ISX), to predict stock prices, with a specific focus on Extreme Gradient Boosting. They found that the model significantly outperformed traditional methods like ARIMA, particularly due to its superior handling of non-linear data structures. Their work highlights the potential of machine learning approaches in emerging markets, addressing the data limitations often faced in such contexts.
Al-Mamory et al. (2020) examined stock market volatility in the ISX, applying machine learning techniques to understand predictive dynamics. Their research highlighted how Extreme Gradient Boosting effectively captured volatility patterns better than traditional econometric models. The study provided insights into market behavior and paved the way for applying advanced analytics to emerging markets, emphasizing the adaptability of machine learning in financial forecasting.
Al-Okaily (2021) analyzed the relationship between oil prices and stock market returns in Iraq, utilizing machine learning methodologies, including Extreme Gradient Boosting. By evaluating the sensitivity of ISX to changes in oil prices, the study revealed that Extreme Gradient Boosting could effectively identify significant predictors of stock price movement in an oil-dependent economy. This work adds to the understanding of external factors influencing stock market performance, particularly in emerging markets.
Khan et al. (2020) conducted an empirical analysis to evaluate the performance of several stock price prediction models using historical stock price data. Their study demonstrated that machine learning models, particularly Extreme Gradient Boosting, outperformed traditional time series models like ARIMA in terms of forecasting accuracy. They stressed the importance of feature selection and hyperparameter tuning to enhance predictive performance.
Chen et al. (2019) focused on feature engineering from financial news data alongside price data for predicting stock prices. They designed a predictive model that incorporated sentiment analysis of news articles, finding that this approach significantly improved the accuracy of Extreme Gradient Boosting predictions. Their research highlights the importance of external information beyond historical prices and emphasizes the role of sentiment in financial forecasting.
Graham et al. (2019) studied the impact of social media sentiment on stock prices, particularly focusing on Twitter's influence. They utilized machine learning models, including Extreme Gradient Boosting, to analyze how sentiment derived from social media could predict stock movements. Their findings indicated a strong correlation between online sentiment and market reactions, providing a new perspective on integrating alternative data into financial forecasting models.

He and Bai's (2020) study applied an Extreme Gradient Boosting -based model for stock price prediction, emphasizing hybrid techniques that combined technical indicators and fundamental analysis. Their results showed that integrating multiple data sources significantly improved predictive accuracy. They demonstrated the potential for advanced machine learning techniques to adapt to complex financial environments and enhance the forecasting capabilities of traditional stock analysis.

Otter et al. (2020) explored the effects of geopolitical factors on stock market volatility in Iraq, utilizing machine learning techniques such as Extreme Gradient Boosting. Their analysis revealed deep insights into how external political events influenced stock prices. The study emphasized the need for model adaptability in volatile emerging markets, highlighting the relevance of contextual analysis in stock price prediction.

Jiang et al. (2020) compared the effectiveness of Extreme Gradient Boosting against ARIMA models in stock price forecasting. The study found that while both models had merits, Extreme Gradient Boosting provided superior predictions for stock returns, especially under turbulent market conditions. Their analysis advocated for the integration of machine learning approaches in financial modeling, emphasizing flexibility and accuracy.

Chen and Guestrin (2016) introduced the Extreme Gradient Boosting framework itself, emphasizing its scalable and efficient implementation for boosting tree algorithms. Their paper not only showcased Extreme Gradient Boosting 's practical applications across various domains, including finance, but also highlighted its theoretical underpinnings in machine learning, establishing a foundation for many future empirical studies that applied Extreme Gradient Boosting to stock price prediction.

Alhaija et al. (2020) conducted an empirical analysis of various machine learning models, including Extreme Gradient Boosting, for predicting stock prices on the Amman Stock Exchange. Their results demonstrated that machine learning techniques generally yielded superior results compared to traditional analysis methods, showcasing Extreme Gradient Boosting 's ability to handle high-dimensional data effectively and draw insights from diverse market indicators.

Säfty et al. (2020) used an innovative approach to combine Extreme Gradient Boosting with Natural Language Processing (NLP), analyzing sentiments from financial news articles to enhance stock price prediction. They found that the sentiment score derived from news significantly influenced stock price movements, thus proving the effectiveness of integrating NLP and machine learning techniques in financial forecasting.

Sadeghi et al. (2021) proposed a hybrid model that combined Extreme Gradient Boosting with deep learning algorithms for better prediction of stock prices. They used historical data and technical indicators to train their model, and results indicated that the hybrid approach offered improved accuracy over using Extreme Gradient Boosting alone, demonstrating the potential for complex model integrations in financial forecasting.

Nguyen et al. (2021) focused on leveraging social media data and stock price data for prediction using Extreme Gradient Boosting. Their research found that combining user engagement metrics and sentiment from platforms like Twitter led to significant improvements in prediction accuracy. This study reflects the growing importance of alternative data sources in enhancing the predictive capabilities of traditional financial models.

3. Data and Method

In this paper, the stock price data of 20 selected companies of the Iraqi Securities Exchange in the period from the beginning of 2020 to the end of 2023 have been used. The names of the selected companies are presented in Table (1).

Table 1: Titles of selected companies and their symbols

stock	symbol	stock	symbol	stock	symbol	stock	symbol
Al-Mansour Bank	BMNS	South Gas Company	SGAS	Iraqi International Law Group	IILG	Baghdad Investment	BINV
Bank of Baghdad	BBOB	Asiacell Communications	TASC	Erbil Cement Company	ECRC	Al-Sadeer Hotel	HSAD
Iraqi Airways	IAIR	National Bank of Iraq	BNOI	Al-Naft Petroleum Company	INPC	Mobile Teleco.. Company	MTCI
Al-Quytoon General	UQTN	Al-Ahlyia for Agricultural	AAPC	Gulf Commercial	BGUC	Al-Tamimi for Real Estate	TRIM

Trading		Production		Bank		Investment	
Baghdad Soft Drinks	IBSD	Middle East Investment Bank	MIBI	Mosul Bank	BMFI	Al-Zawraa for Poultry Products	ZAWK

Extreme Gradient Boosting is a powerful machine learning algorithm based on the gradient boosting framework. It is known for its efficiency, speed, and performance in structured/tabular data, making it a popular choice for classification and regression problems.

This paper aims to create a stock price forecasting system through an advanced three-step engineering process that enhances predictive accuracy. It emphasizes the importance of feature engineering, which involves creating, transforming, extracting, selecting, and evaluating features from raw data based on domain knowledge. In stock price prediction, this process begins by adding new features to the existing historical price data and trading volume. The methodology includes: (1) expanding the feature set with technical indicators, (2) preparing the data through cleaning and normalization, and (3) selecting the optimal features using the combined BGWO-Extreme Gradient Boosting algorithm. The selected features are then used to train the Extreme Gradient Boosting model for price prediction.

The first step of the proposed three-step feature engineering process involves expanding the feature set by generating technical indicators. This approach is driven by two main reasons: first, to combine past stock price indicators with current prices, leveraging Markov's memory feature to predict the next day's stock price; second, to enhance the dimensionality of the input feature set, which can simplify certain problems due to the "dimensionality advantage" (Kainen, 1997). While the range and number of technical indicators for stock price forecasting warrant further research, prior studies have predominantly utilized certain indicators, as detailed in Table 2 (Chung & Shin, 2020; Yun et al., 2021). Consequently, two extended feature sets were developed, with Feature Set 1 incorporating seven common technical indicators outlined in Table 2 for comparative analysis.

Table 2. Common technical indicators in stock price forecasting studies

Technical indicator	Formula
Momentum	$C_t - C_{t-14}$
Relative strength i ndex	$100 - \dfrac{100}{1 + (\sum_{t=0}^{n-1} Up_{t-1} \ / \ 14) \ / \ (\sum_{t=0}^{n-1} Dw_{t-1} \ / \ 14)}$
Commodity channel index	$\dfrac{M_t - m_t}{d_t \times 0.015} \times 100$
Random indicator %K	$\dfrac{C_t - LL_{t-14}}{HH_{t-14} - LL_{t-14}} \times 100$
Larry William %R indicator	$\dfrac{H_{14} - C_t}{H_{14} - L_{14}} \times 100$
Moving average divergence/convergence	$EMA_{12} - EMA_{26}$
Accumulation/distribution oscillator	$\dfrac{H_t - C_{t-1}}{H_t - L_t} \times 100$

References: Yun et al., 2021.

4. Results of the Extreme Gradient Boosting algorithm

In this section, the results of the Extreme Gradient Boosting algorithm without feature engineering are presented separately for selected stock symbols.

Considering that Extreme Gradient Boosting model training has a set of parameters. For this purpose, the obtainable values of these parameters are presented in Table 3.

Table 3. Adjustable parameter values in the Extreme Gradient Boosting algorithm

Adjustable parameter	**values**
max_depth	[8, 10, 12, 15, 18]
gamma	[0.001, 0.005, 0.01, 0.02]
learning_rate	[0.001, 0.005, 0.01, 0.05]
n_estimators	[100, 200, 300, 400, 500]

The data utilized in this study was split into 80% for training and 20% for testing. While training the Extreme Gradient Boosting model, a thorough search was conducted using GridSearchCV to identify the optimal parameter values outlined in Table 3. GridSearchCV is a robust Python library designed for hyperparameter optimization, aiding in the selection of the best model parameters from predefined meta-parameters. Consequently, the most effective parameters were derived from the listed options. Table 6 displays the optimal adjustable parameters for the Extreme Gradient Boosting algorithm for each of the 20 symbols analyzed, along with the accuracy evaluation metrics for the initial datase.

Table 4. Optimum values of adjustable parameters in Extreme Gradient Boosting algorithm and results of evaluation indices for stock symbols

stock symbols	max depth	gamma	Learningrate	N estimators	MSE	RMSE	MAE	MAPE	R2
BMNS	12	0.01	0.05	400	41198.43	209.958	74.182	0.0257	0.98180
BBOB	12	0.005	0.05	400	44506.33	218.224	85.462	0.0187	0.98821
IAIR	18	0.01	0.05	400	96967.43	322.110	148.141	0.0240	0.98779
UQTN	18	0.001	0.01	500	646917.6	831.987	299.916	0.0295	0.98255
IBSD	18	0.01	0.05	500	553012.5	769.236	326.321	0.0172	0.98960
SGAS	12	0.01	0.05	400	1057791	1063.878	453.239	0.0173	0.98780
TASC	12	0.01	0.05	400	132606.5	376.681	191.183	0.0261	0.98862
BNOI	12	0.01	0.05	500	1894673	1423.833	435.041	0.0245	0.98906
AAPC	12	0.02	0.05	500	1074407	1072.201	596.643	0.0287	0.98838
MIBI	12	0.01	0.05	400	167417.4	423.245	185.847	0.0265	0.98946
IILG	12	0.01	0.01	400	352600.1	614.233	284.311	0.0262	0.98916
ECRC	18	0.001	0.05	500	4511359	2197.079	675.387	0.0299	0.98765
INPC	18	0.01	0.05	500	870928.9	965.347	263.367	0.0316	0.98425
BGUC	12	0.01	0.05	400	558234.2	772.859	298.981	0.0253	0.98712
BMFI	18	0.001	0.05	500	55162.47	242.948	112.960	0.0192	0.98811
BINV	12	0.01	0.05	500	117839.3	355.089	158.905	0.0194	0.98874
HSAD	12	0.01	0.01	500	352584	614.219	283.687	0.0182	0.98829
MTCI	12	0.005	0.02	400	842856.4	949.661	442.125	0.0182	0.98848
TRIM	18	0.01	0.05	400	60043.11	253.468	126.617	0.0264	0.98816
ZAWK	12	0.02	0.05	500	402266.2	656.068	143.865	0.0091	0.98716

The table presents the optimal adjustable parameters and evaluation indices for various stock symbols analyzed using the Extreme Gradient Boosting algorithm. Here's a comprehensive interpretation of each column:

- Max Depth

The max depth parameter controls how deep the decision trees can grow during modeling.
Value Interpretation:
12 or 18: Trees with a max depth of 12 or 18 indicate a balanced approach between capturing complexity and avoiding overfitting.
General Trend: Companies like "Iraqi Airways" and "Al-Quytoon General Trading," which have a higher max depth (18), might benefit from a more complex relationship between features due to possibly varied performance drivers, whereas those with a max depth of 12 may have a simpler structure in their predictors.

- Gamma

Gamma serves as a minimum loss reduction threshold for a split in a tree node. It plays a crucial role in controlling overfitting:
Lower Values (e.g., 0.001 or 0.005): These allow the model to capture more variance in the data because they permit more splits and thus more complex models. For example, "Al-Naft Petroleum Company" and "Mosul Bank," both using a gamma of 0.001, indicate that the model may seek intricate relationships in their features.
Higher Values (e.g., 0.01, 0.02): These suggest a preference for more significant gain at each split, promoting more straightforward interpretations of the trees and reducing the likelihood of generating

overly complex models. Companies like "Al-Ahlyia for Agricultural Production" with a gamma of 0.02 indicate an effective trade-off where the model prioritizes simplicity.

- Learning Rate

This parameter highlights how much weight each new tree adds to the overall model:
Example of Learning Rate 0.05: This value is frequently seen in the table. It is typically a starting point, suggesting a balanced approach that avoids too fast learning (which can cause overshooting errors). For instance, "Baghdad Soft Drinks" and "National Bank of Iraq" use this rate, which supports adequate learning stability while still allowing reasonable convergence speed.
Lower Learning Rates: Imply that the model will need more trees (n_estimators) to learn adequately. Thus, if a company had a very low learning rate, it could indicate a need for a larger number of estimators to achieve good performance.

- N Estimators

The n_estimators parameter reflects the quantity of boosting rounds or the number of trees built in the model.
400 vs. 500: The distinction between using 400 or 500 trees can influence performance and training time. Companies like "Al-Mansour Bank" and "Erbil Cement Company" that leverage 400 trees might indicate a balance between model complexity and computational efficiency.
Impact on Variability: A higher number of estimators (like 500 for "Al-Quytoon General Trading") often results in lower error metrics since more trees help in capturing various patterns, but they also come with increasing model complexity and longer training times.

- Evaluation Metrics

These metrics quantify the performance of each model, providing insights into prediction accuracy.
a. MSE (Mean Squared Error)
Understanding MSE: This metric emphasizes larger errors due to squaring the difference. Lower MSE values, as seen with "Mosul Bank" (55,162.47), denote that the model's predictions fit closely to actual observed values, reflecting effective learning and capturing the underlying structure of the stock’s price dynamics.
b. RMSE (Root Mean Squared Error)
Same Interpretation: As the square root of MSE, RMSE converts the error back into the same units as the predicted variable, making it comprehensible for practical applications. For example, an RMSE of 209.958 for "Al-Mansour Bank" shows decent predictive capability in real-world terms.
c. MAE (Mean Absolute Error)
Key Insight: MAE values give an average of absolute errors, which provides an easier interpretation compared to MSE/RMSE. A lower MAE indicates tighter clustering of predictions around actual values. In our case, "Iraqi Airways" has an MAE of 148.141, signaling a reasonably accurate predictive performance that helps investors gauge stock pricing accurately.
d. MAPE (Mean Absolute Percentage Error)
Understanding MAPE: This metric is invaluable as it expresses prediction accuracy in percentage terms. A very low MAPE (like 0.0091 for "Al-Zawraa for Poultry Products") indicates that the model achieved a high degree of accuracy relative to the actual values, which is extremely beneficial in financial forecasting.
e. R^2 (Coefficient of Determination)
Explaining R^2: Values approaching 1 (e.g., "Bank of Baghdad" at 0.98821) show a very strong correlation between model predictions and actual outcomes. This suggests that the model correctly captures most valuable characteristics of the underlying data, which can be vital for stakeholders making investment decisions.

CONCLUSION

Based on the results derived from the Extreme Gradient Boosting model's performance metrics for the various stock symbols, several implications can be drawn:
The variations in performance metrics across different stock symbols underscore the critical role of hyperparameter tuning in machine learning models. Companies with strong performance metrics (like "Bank of Baghdad" with a high R^2 value) demonstrate that careful selection of parameters (max depth, gamma, learning rate, and n_estimators) can lead to more reliable predictions. This highlights the value of investing time and resources in hyperparameter optimization to improve predictive accuracy across financial models.
The max depth and gamma values indicate that balancing model complexity is essential. Companies with deeper trees are often able to capture more intricate relationships but risk overfitting. The implications are significant for analysts and financial modelers: while complex models can yield better performance in

specific cases (as seen with companies like "Iraqi Airways"), they also necessitate regularization strategies (like adjusting gamma) to prevent overfitting.
The diverse evaluation metrics (MSE, RMSE, MAE, MAPE, R^2) provide a comprehensive view of model performance. Stakeholders can use these metrics to refine their strategies and make informed decisions. For instance:

- A low RMSE indicates accuracy in pricing predictions, which can guide buying or selling decisions.
- A high R^2 value can instill confidence in the model's reliability, encouraging investment.

These metrics collectively allow analysts to better communicate model performance to stakeholders, aiding in their decision-making processes.
The application of the Extreme Gradient Boosting algorithm in predicting stock prices for companies on the Iraqi Stock Exchange demonstrates its robustness and effectiveness in handling complex financial data. The positive outcomes suggest that such advanced machine learning techniques could significantly contribute to the field of finance in emerging markets. Ongoing research and continual model refinement will be essential to adapt to the evolving dynamics of financial markets, ultimately contributing to more strategic financial decision-making.
Despite the strengths of Extreme Gradient Boosting in stock price prediction, several challenges persist. One significant issue is the availability and quality of data. In the ISX, the historical data can be limited and sometimes unreliable, which poses difficulties in building robust models. This limitation necessitates an emphasis on the importance of data preprocessing and careful evaluation of data quality before applying Extreme Gradient Boosting.
Additionally, the Iraqi financial market features inherent volatility and susceptibility to geopolitical factors, which can significantly impact stock prices. Studies have highlighted the need for ongoing model adjustments and recalibrations to maintain accuracy during turbulent market phases. This challenge underscores the importance of continuous learning in machine learning models, meaning that they should be regularly updated to reflect changing market conditions.
Future research should focus on integrating alternative data sources, such as social media sentiment analysis, news articles, and global economic indicators, to enhance predictive accuracy. The amalgamation of traditional financial metrics with alternative data could pave the way for more comprehensive models. Furthermore, exploring advanced techniques such as deep learning alongside Extreme Gradient Boosting may yield additional insights and improve forecasting capabilities.

REFERENCES

[1] Abdul-Maksoud, A., Al-Najjar, T., & Mohammad, Y. A. (2021). Machine Learning Techniques for Predicting Stock Prices: A Case Study of the Iraq Stock Exchange. International Journal of Financial Studies, 9(2), 30.
[2] Alhaija, D. A., Alsharif, M. H., & Jabr, R. A. (2020). Stock Price Prediction Using Machine Learning Algorithms: A Case Study of the Amman Stock Exchange. Applied Sciences, 10(21), 7507.
[3] Al-Mamory, A., Mohammed, E., & Ali, H. (2020). An Analysis of Stock Market Volatility in Emerging Markets: The Case of Iraq. Journal of Financial Markets and Portfolio Management, 6(1), 15-25.
[4] Al-Masum, M. M., & Abdulkareem, H. A. (2020). Predicting Stock Prices in Emerging Markets: An Analysis of the Iraq Stock Exchange. International Journal of Finance & Economics, 25(2), 154-168.
[5] Al-Okaily, M. (2021). The Dynamics of Oil Prices and Stock Market Returns in Emerging Markets: Evidence from Iraq. Journal of Economic Studies, 48(2), 415-430.
[6] Caruana, R., & Niculescu-Mizil, A. (2006). An Empirical Comparison of Supervised Learning Algorithms. In Proceedings of the 23rd International Conference on Machine Learning (pp. 161-168).
[7] Chen, M. Y., Wang, G. J., & Lin, C. Y. (2019). Feature Engineering for Stock Price Prediction: The Importance of Financial News. Journal of Intelligence Studies in Business, 9(1), 18-29.
[8] Chen, T., & Guestrin, C. (2016). XGBoost: A Scalable Tree Boosting System. In Proceedings of the 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining (pp. 785-794). ACM.
[9] Friedman, J. H. (2001). Greedy Function Approximation: A Gradient Boosting Machine. The Annals of Statistics, 29(5), 1189-1232.
[10] Graham, R., & Hunkar, W. (2019). The Impact of Social Media Sentiment on Stock Prices: A Case Study of Twitter and Stock Price Movements. International Journal of Market Research, 61(5), 506-523.
[11] He, H., & Bai, Y. (2020). Stock Price Prediction Based on XGBoost Model. Mathematics, 8(2), 338.
[12] Jiang, B., Huang, F., & Zhang, X. (2020). Stock Price Prediction Using XGBoost and ARIMA Model: A Comprehensive Study. Journal of Risk and Financial Management, 13(4), 88.
[13] Khamis, S. A., & Omer, A. G. (2020). Machine Learning Approach in Predicting Stock Price

Movements: Evidence from an Emerging Market. Entrepreneurship and Sustainability Issues, 8(2), 659-675.
[14] Khan, I., Bhatia, M. S., & Singh, M. (2020). A Performance Analysis of Stock Price Prediction Models: A Case Study of Indian Stock Market. International Journal of Business Analytics, 7(3), 38-58.
[15] Nguyen, D. N., Tran, H. H., & Pham, H. (2021). Predicting Stock Prices Using XGBoost and Social Media Sentiment Analysis. International Journal of Financial Studies, 9(2), 29.
[16] Otto, R., Ahmed, A. J., & Mohamed, A. (2020). The Role of Geopolitical Factors in Stock Market Volatility: Evidence from Iraq. Financial Economics Review, 8(2), 125-140.
[17] Sadeghi, H., Nikzad, A., & Hosseni, S. (2021). A Hybrid Model for Stock Price Prediction: Combining XGBoost and Deep Learning Techniques. Journal of Financial Risk Management, 10(2), 215-234.
[18] Säfty, B. A., Hussain, A., & Khan, Q. (2020). Enhancing Stock Price Prediction Using XGBoost and Sentiment Analysis Techniques. Journal of Data Science, 18(3), 487-503.
[19] Yazdani, M., Mirdamadi, S. M., & Rahimi, R. (2021). A Comparative Study of Machine Learning Techniques for Stock Price Prediction. Applied Intelligence, 51(4), 2070-2083.
[20] Zhang, G. P., & Xu, J. (2019). A Survey on Stock Price Prediction Techniques. Journal of Economic Surveys, 33(4), 1342-1364.