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XFinInsight-HI: A Human-in-the-Loop Explainable Artificial Intelligence Framework for Trustworthy Stock Market Prediction Using Yahoo Finance Data

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Abstract

Artificial Intelligence (AI) has become an important technology for stock market prediction by learning complex patterns from historical financial data. Although machine learning and deep learning models have achieved promising predictive performance, they often operate as black-box systems, limiting transparency, investor trust, and practical adoption in financial decision-making. Existing Explainable Artificial Intelligence (XAI) approaches mainly provide post-hoc explanations without incorporating expert knowledge into the prediction process. To address these limitations, this paper proposes XFinInsight-HI, a Human-in-the-Loop Explainable Artificial Intelligence framework for trustworthy stock market prediction using historical data collected from Yahoo Finance. The proposed framework performs data preprocessing and extracts technical indicators, including Relative Strength Index (RSI), Moving Average Convergence Divergence (MACD), Simple Moving Average (SMA), Exponential Moving Average (EMA), Bollinger Bands, volatility measures, and volume-based indicators to construct representative financial features. Random Forest, XGBoost, and Long Short-Term Memory (LSTM) models are developed for stock price prediction and evaluated using Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and Directional Accuracy. Experimental results show that XGBoost achieves the best predictive performance with an RMSE of 9.23 USD and an MAE of 5.86 USD on the held-out test dataset. SHAP is employed to generate both global and local explanations, demonstrating that moving average-based technical indicators contribute most significantly to stock price prediction. Furthermore, the proposed Human-in-the-Loop validation mechanism enables financial analysts to review uncertain predictions and provide corrective feedback, reducing the RMSE from 10.06 USD to 9.28 USD and the MAE from 6.18 USD to 5.60 USD on the review subset. The proposed XFinInsight-HI framework improves prediction reliability, transparency, and user trust by integrating accurate forecasting, explainable AI, and expert validation into a unified decision-support system for intelligent stock market analysis.

Keywords: *Explainable Artificial Intelligence, Yahoo Finance, Stock Market Prediction, Human-in-the-Loop Learning, SHAP, LSTM, XGBoost, Financial Analytics*

1 Introduction

The stock market is generally acknowledged as one of the major factors that determine the economic well-being of a country and has an important place in the global financial environment. Governments, institutional investors, financial analysts, and policymakers regularly track stock market dynamics in order to make conclusions about the economic situation, assess investment opportunities, and create financial strategies [1]. Compared to classical investments like bank deposits and government bonds, the stock market provides an opportunity to earn more profit but with higher risks and uncertainty. The fast development of global financial markets increases their importance from an economic point of view. In 2022, the total capitalization of stock markets worldwide amounted to over USD 70.75 trillion, which confirms the growing necessity of using intelligent financial decision-support systems when working with highly dynamic markets [2].

Prediction of stock market dynamics is a difficult task of scientific research for a long time because there are many factors affecting stock prices: company performance, economic situation, investor behavior, political events, and others [1]. All these factors interrelate in a complicated way leading to high volatility of stock prices.

The recent development of Artificial Intelligence (AI), Machine Learning (ML) and Deep Learning (DL) has significantly revolutionized the stock market prediction by providing predictive models which can be fed with large-scale financial data and learn the complex non-linear relationships between them [3],[4],[5]. Ensemble-learning algorithms like Random Forest and eXtreme Gradient Boosting (XGBoost) are shown to be able to capture the temporal dependency, trend dynamics and market volatility [6] as are deep neural architectures like Long Short-Term Memory (LSTM) networks. These techniques are typically more effective than traditional statistical forecasting methods because they have the ability to learn highly complex relationships between past price movements, trading volume, and technical indicators. Consequently, AI-driven predictive systems are increasingly being adopted within algorithmic trading platforms, robo-advisory services, and institutional investment frameworks.

Despite these great achievements, there are still several key challenges to address in current AI-based stock forecasting systems. Financial markets are highly volatile, have structural breaks and are subjected to very dynamic economic environments, which often limits the generalization power of predictive models. Additionally, the stock market data is frequently noisy, with missing data and non-stationary patterns that pose a higher risk of overfitting and impact prediction accuracy when applied to new market scenarios [7],[8]. While significant effort has been made to build increasingly complex machine learning architectures for improved prediction, far less effort has been dedicated to building models that provide transparent, interpretable and trustworthy predictions that are useful for making real world financial decisions.

One of the major limitations of the existing AI-based financial forecasting systems is the issue of interpretability. The advanced machine learning and deep learning algorithms usually work in a black-box way, producing very accurate forecasts without giving any explanations to the underlying reasoning process. In the financial application context, where the decisions made may have a large impact on the economy, the lack of interpretability greatly undermines investor trust and regulatory acceptance. The growing demand of financial analysts, portfolio managers, and regulators for AI tools that could give accurate forecasts and explain what financial factors affect these forecasts has led to a rise in the importance of the field called Explainable Artificial Intelligence (XAI).

Among different XAI methods, SHapley Additive exPlanations (SHAP) [9],[10],[11],[12] and Local Interpretable Model-agnostic Explanations (LIME) [13],[14],[15],[16] have emerged as two of the most popular and widely used frameworks for interpreting complicated machine learning models. While SHAP offers both global and local feature attributions through estimating the contribution of each of the input variables in the individual predictions, LIME builds a locally interpretable surrogate model to explain each prediction instance. Several prior works have shown that these frameworks can be useful in discovering relevant technical factors, trading volumes, momentum signals, and characteristics of the market which influence the results of the prediction. However, most of the research work that has explored the potential of XAI for predicting stocks stops with the generation of the explanation without validating the explanations through financial domain expertise.

While current XAI techniques may enhance transparency of models, they give explanations only post-prediction. Research works make the assumption that the provided explanations are valid and exclude financial experts from the process of decision making. In reality, experienced financial analyst can detect invalid predictions, check if the provided explanations are economic sense and make a useful remark based on present market situation. Hence, explanation is not enough by itself and validation by an expert is needed as well.

To solve this constraint, this study introduces XFinInsight-HI, a Human-in-the-Loop Explainable Artificial Intelligence system for trustworthy stock market forecast based on Yahoo Finance data. In the first phase, the proposed framework collects historical Open-High-Low-Close-Volume (OHLCV) data from Yahoo Finance and extracts important technical indicators, including Relative Strength Index (RSI), Moving Average Convergence Divergence (MACD), Simple Moving Average (SMA), Exponential Moving Average (EMA), Bollinger Bands, rolling volatility and volume-based indicators. Then three prediction models Random Forest, XGBoost and LSTM are created to anticipate stock market activity. SHAP provides local and global explanations for model predictions. Finally, a Human-in-the-Loop expert validation layer enables financial analysts to inspect uncertain forecasts, assess the provided explanations and give input to improve future model performance.

Unlike existing stock market prediction frameworks that stop after generating explanations, the proposed XFinInsight-HI framework combines AI prediction, explainability, and expert validation within a single decision-support system. This integration improves prediction reliability, explanation quality, analyst confidence, and the overall trustworthiness of AI-based financial forecasting.

The primary contributions of this work are summarized as follows:

1. A novel Human-in-the-Loop Explainable AI framework (XFinInsight-HI) is proposed for trustworthy stock market prediction using Yahoo Finance data.
2. A comprehensive feature engineering pipeline is developed using OHLCV data and multiple technical indicators, including RSI, MACD, SMA, EMA, Bollinger Bands, volatility, and volume-based features.
3. Random Forest, XGBoost, and LSTM models are implemented and compared to identify the most effective prediction model.
4. SHAP-based explainability is integrated to provide both global and local interpretations of model predictions.
5. A Human-in-the-Loop validation mechanism enables financial experts to verify AI explanations, provide confidence scores, and refine predictions through structured feedback.
6. The proposed framework improves not only prediction performance but also transparency, interpretability, and trustworthiness, making it suitable for intelligent financial decision-support systems.

The remainder of this paper is organized as follows. Section 2 reviews related work on machine learning for stock prediction and explainable AI in finance. Section 3 presents the proposed XFinInsight-HI framework, including the data pipeline, predictive models, SHAP explainability layer, and the human-in-the-loop validation mechanism, together with the associated algorithms. Section 4 reports and discusses the results. Section 5 concludes the paper and outlines directions for future work.

2 Related Work

There have been many studies on stock market predictions based on statistical learning, machine learning (ML) approaches, and deep learning (DL) methods. However, early studies on stock market predictions mainly involved stock price or market trend prediction through traditional machine learning methods. One of the most efficient ensembles learning methods used for financial prediction is XGBoost, created by Chen & Guestrin [17]. The reason why XGBoost was one of the most efficient was due to its ability to regularize and handle noisy data in the market environment.

The use of regression methods has also received much attention in predicting stock prices. Khan et al. [18] constructed a regression method based on historical data from Yahoo Finance from several stock exchanges and achieved good prediction results based on the Mean Absolute Error (MAE) and Root Mean Square Error (RMSE) criteria. But their study mainly focused on numerical prediction results while ignoring model explainability and decision-making transparency. Likewise, Zhong et al. [19] suggested an extensive data mining technique by using PCA and ANN for daily stock return predictions. Their dimensionality reduction method helped in enhancing the accuracy of the classification and portfolio gain but failed to deal with prediction result explanation.

Support Vector Machine (SVM) algorithm has been widely used in forecasting stock market trends due to its excellent generalization property. Lin et al. [20] have further advanced SVM algorithm in predicting stock market trends by applying a correlation-based feature selection strategy that has increased prediction performance and selected relevant features from the stock market data of Taiwan. Similarly, Ratto et al. [21] have used technical indicators along with SVM for predicting the movement of NASDAQ stocks and dealing with the issue of imbalanced data. Although the proposed model was successful in achieving moderate prediction performance, it is still confined to binary trend prediction.

The rapid advancement of deep learning has significantly influenced financial time-series prediction by enabling models to capture temporal dependencies within historical market data. [22] introduced the Long Short-Term Memory (LSTM) architecture, which effectively overcomes the vanishing-gradient problem associated with conventional recurrent neural networks. In this design, Sang and Li [23] propose to include attention mechanisms into the LSTM networks to better capture important past trading patterns and increase forecasting performance. Similarly, Oukhouya et al. [24] evaluated XGBoost, LSTM and hybrid LSTM-XGBoost models across worldwide stock markets, and showed that hybrid architectures increased the forecasting resilience and predictive accuracy compared with individual learning models. However, even with these breakthroughs, the majority of the current machine learning and deep learning frameworks are black-box systems that provide very accurate predictions but do not explain the underlying reasoning process. The increasing use of Artificial Intelligence in financial services has thus accelerated the research on Explainable Artificial Intelligence (XAI). XAI's primary goal is to improve transparency by identifying the impact of input variables on prediction outcomes, thereby boosting user confidence and regulatory acceptance. Among the available XAI techniques Lundberg and Lee [12] suggested SHapley Additive exPlanations (SHAP), a game-theoretic method that computes feature contributions for global and local model interpretation. SHAP is one of the most popular explainability methods for tree-based and ensemble learning algorithms because of its theoretical consistency and computational efficiency. Ribeiro et al. [25] proposed the Local Interpretable Model-agnostic Explanations (LIME) framework which constructs interpretable local surrogate models to explain individual predictions regardless of the underlying learning algorithm. Several recent studies have integrated explainability techniques into stock market prediction. Deng et al. [26] combined XGBoost with SHAP to forecast Chinese stock index movements and demonstrated that investor sentiment variables substantially influenced prediction performance. Jabeur et al. [27] applied SHAP interaction values to XGBoost-based gold price forecasting and revealed complex nonlinear interactions among macroeconomic indicators that conventional feature importance methods failed to identify. Furthermore, Wallapure Manikrao et al. [28] integrated SHAP and LIME with LSTM-based stock market prediction and reported improved predictive performance while maintaining interpretable explanations.

Table 1 Summary of Existing Stock Market Prediction Frameworks

Authors (Ref.)	**Dataset**	**Data Time Frame**	**Approach**	**Evaluation Metrics**	**Prediction Type**	**Integration with XAI**
[29]	Goldman Sachs Group Inc.	1999–2014	LR, LASSO	RMSE	Price	No
[30]	Brazilian, American, and Chinese stocks	2002–2017	SVM	RMSE	Price	No
[18]	Shenzhen Development Stock	2007	Logistic Regression	Accuracy	Trends	No
[19]	New York, London, NASDAQ, and Karachi	1998–2018	Regression-based Model	MAE, RMSE	Price	No
[31]	S&P 500	2003–2013	PCA, ANN	Accuracy	Price	No
[20]	NASDAQ	Not Mentioned	SVM	Accuracy	Trends	No
[32]	China Stock Market	2008–2015	MLP, RNN, LSTM, NB, DT	Accuracy	Trends	No
[33]	BSE SENSEX	2012–2018	ANN, SVM	MAE, MAPE	Trends	No
[34]	Apple, Google, and Microsoft	2015–2016	Recurrent-CNN	Accuracy	Trends	No
[35]	Istanbul and NASDAQ	2007–2014	SVM, ANN	Accuracy	Trends	No
[36]	S&P 500	2020	Gradient Boosting	Average Precision	Price	Yes (LIME)
[37]	S&P 500, NI225, XU100, KOSPI	10 Years	ANN	Accuracy	Price	Yes (LIME)

2.1 Research gap

Although many studies have developed machine learning and deep learning models for stock market prediction, most of them mainly focus on improving prediction accuracy. Traditional machine learning models often struggle to capture the complex and dynamic nature of financial markets, while deep learning models generally function as black-box systems with limited interpretability. Recent studies have incorporated explainable AI techniques such as SHAP and LIME to provide feature-level explanations, but these explanations are usually generated only after prediction and are not validated by financial experts. Moreover, existing frameworks do not provide a mechanism to incorporate expert knowledge or feedback into the prediction process, limiting their reliability and practical use in real-world financial decision-making.

To address these limitations, this study proposes XFinInsight-HI, a Human-in-the-Loop Explainable Artificial Intelligence framework for trustworthy stock market prediction. The proposed framework combines historical Yahoo Finance data, technical indicators, and multiple prediction models to generate accurate stock price forecasts. SHAP is used to provide clear and transparent explanations for each prediction, while a Human-in-the-Loop expert validation layer allows financial analysts to review predictions, verify the generated explanations, and provide feedback. This feedback is incorporated into periodic model refinement, improving prediction reliability, transparency, and user trust. By integrating prediction, explainability, and expert validation into a single framework, the proposed approach offers a more practical and trustworthy solution for intelligent stock market decision support.

3 Research Methodology

The proposed XFinInsight-HI (Human-in-the-Loop Explainable Artificial Intelligence) framework is designed as a comprehensive five-stage pipeline for trustworthy stock market prediction. The framework integrates data acquisition and preprocessing, technical indicator-based feature engineering, multi-model predictive learning, SHAP-based explainability, and a Human-in-the-Loop (HITL) expert validation mechanism. Unlike conventional AI-based stock forecasting systems that terminate after generating predictions or post-hoc explanations, XFinInsight-HI incorporates financial analysts into the prediction workflow, enabling expert verification, confidence assessment, and iterative model refinement. Figure 1 illustrates the overall architecture of the proposed framework, demonstrating the flow from raw Yahoo Finance data to transparent and analyst-endorsed prediction outcomes.

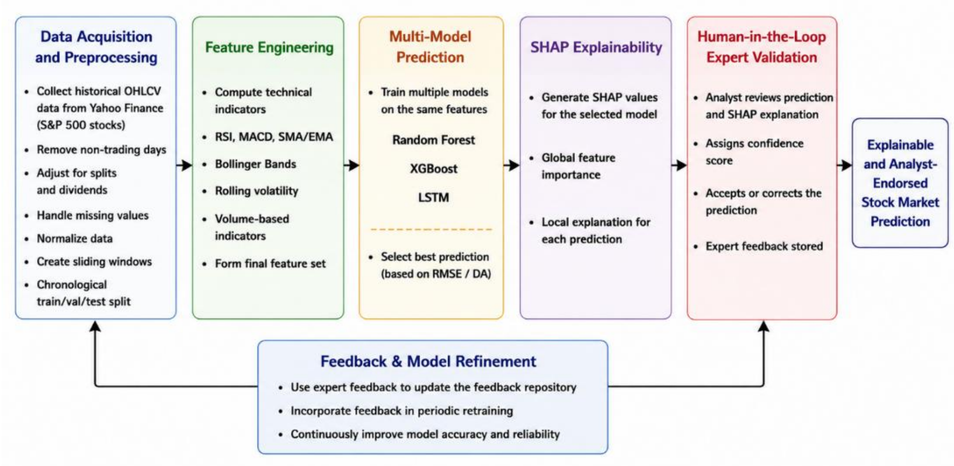

Figure 1. Overall Workflow of the XFinInsight-HI Framework

3.1 Data Acquisition and Preprocessing

Accurate stock market prediction requires high-quality historical data and an effective preprocessing strategy. Financial time-series data often contain missing values, non-trading days, stock splits, and dividend adjustments, which may introduce inconsistencies and reduce the predictive performance of machine learning models. Therefore, appropriate preprocessing is performed to ensure data quality and improve model reliability.

In this study, historical daily Open, High, Low, Close, and Volume (OHLCV) data are collected from Yahoo Finance for companies listed in the S&P 500 index. The collected dataset can be represented as

$$D = \{(O_t, H_t, L_t, C_t, V_t)\}_{t=1}^{N}, \qquad (1)$$

where O_t, H_t, L_t, C_t, and V_t represent the opening, highest, lowest, closing prices, and trading volume on day t, respectively, and N is the total number of trading days.

Initially, non-trading days are removed to maintain the continuity of the time series. Historical prices are then adjusted for stock splits and dividend distributions to ensure consistency throughout the observation period. Missing values are handled using the forward-fill method, in which the missing value is replaced by the previously available observation. If a trading window contains excessive missing values, it is discarded to avoid introducing inaccurate market information.

After data cleaning, technical indicators are extracted from the OHLCV data and combined with the original market variables to create the feature set. Since the features have different numerical ranges, they are normalized before model training. In this work, Min-Max normalization is applied to scale all features into the range of 0 to 1, which is expressed as

$$x_i' = \frac{x_i - x_{\min}}{x_{\max} - x_{\min}}, \qquad (2)$$

where x_i is the original feature value, and $x_{\min}$ and $x_{\max}$ are the minimum and maximum values of the corresponding feature. This normalization improves training stability and accelerates model convergence.

Next, the normalized data are transformed into fixed-length sliding windows so that each input sample contains historical observations from the previous w trading days. The input sequence is represented as

$$X_t = \{x_{t-w+1}, x_{t-w+2}, \dots, x_t\}, \qquad (3)$$

where w denotes the look-back window length.

Finally, the processed dataset is divided into training, validation, and testing sets using a chronological walk-forward split. This approach preserves the temporal order of stock market data and prevents look-ahead bias, providing a realistic evaluation of the proposed prediction framework under real trading conditions.

3.2 Multi-Model Prediction

Stock market prediction is a complex task due to the nonlinear and dynamic nature of financial time-series data. To improve prediction performance and evaluate different learning capabilities, three complementary machine learning and deep learning models, namely Random Forest (RF), eXtreme Gradient Boosting (XGBoost), and Long Short-Term Memory (LSTM), are employed. Random Forest and XGBoost are effective for learning nonlinear relationships among engineered technical indicators, whereas LSTM captures long-term temporal dependencies present in sequential stock market data.

Random Forest

Random Forest is an ensemble learning algorithm that constructs multiple decision trees using bootstrap sampling and random feature selection. The final prediction is obtained by averaging the predictions of all decision trees, thereby reducing variance and improving generalization.

The prediction of the Random Forest model is given by

$$\hat{y} = \frac{1}{B}\sum_{i=1}^{B} T_i(x), \qquad (4)$$

where B denotes the total number of decision trees, $T_i(x)$ represents the prediction of the i^{th} decision tree, and $\hat{y}$ is the final predicted output.

XGBoost

XGBoost is a gradient boosting algorithm that sequentially constructs decision trees to minimize prediction errors. Each new tree is trained to correct the residual errors produced by previous trees while incorporating regularization to prevent overfitting.

The final prediction is expressed as

$$\hat{y} = \sum_{k=1}^{K} f_k(x), \qquad (5)$$

where K is the number of boosting trees and $f_k(x)$ denotes the prediction generated by the k^{th} tree.

The objective function optimized by XGBoost is

$$Obj = \sum_{i=1}^{N} l\,(y_i, \hat{y}_i) + \sum_{k=1}^{K} \Omega\,(f_k), \qquad (6)$$

where $l(\cdot)$ represents the loss function, $\Omega(f_k)$ is the regularization term that controls model complexity, and N is the total number of training samples.

Long Short-Term Memory (LSTM)

LSTM is a recurrent neural network designed to capture long-term dependencies in sequential data. Unlike conventional neural networks, LSTM employs memory cells and gating mechanisms to selectively retain or discard historical information, making it highly suitable for financial time-series forecasting.

The forget gate is computed as

$$f_t = \sigma\left(W_f[h_{t-1}, x_t] + b_f\right), \qquad (7)$$

where f_t determines the amount of previous information to retain.

The input gate is calculated as

$$i_t = \sigma(W_i[h_{t-1}, x_t] + b_i), \qquad (8)$$

which controls the amount of new information stored in the memory cell.

The cell state is updated as

$$C_t = f_t C_{t-1} + i_t \tilde{C}_t, \qquad (9)$$

where C_t represents the updated memory state.

Finally, the hidden state is obtained by

$$h_t = o_t \tanh(C_t), \qquad (10)$$

where o_t is the output gate. The hidden state is subsequently used to generate the stock price prediction.

The three models are trained using the same pre-processed dataset and are evaluated using identical training, validation, and testing partitions. The model achieving the best predictive performance is selected for further explainability analysis.

3.3 SHAP-Based Explainability

Although machine learning and deep learning models provide accurate predictions, they often operate as black-box models whose decision-making process is difficult to interpret. To improve transparency and build user trust, the proposed framework employs SHapley Additive exPlanations (SHAP). SHAP is based on cooperative game theory and quantifies the contribution of each input feature toward the final prediction.

For a prediction $f(x)$, SHAP represents the model output as

$$f(x) = \phi_0 + \sum_{i=1}^{M} \phi_i, \qquad (11)$$

where ϕ_0 is the baseline prediction, M denotes the total number of input features, and ϕ_i represents the contribution of the i^{th} feature to the final prediction.

To identify the most influential features across the entire dataset, the global feature importance is computed as

$$Importance_i = \frac{1}{N} \sum_{j=1}^{N} |\, \phi_{ij} \,|, \qquad (12)$$

where N is the number of prediction instances and ϕ_{ij} denotes the SHAP value of feature i for the j^{th} sample.

In addition to global interpretation, SHAP also provides local explanations by displaying the contribution of individual features for a specific prediction. This enables financial analysts to understand why a particular stock movement was predicted and identify the technical indicators that most strongly influenced the decision.

3.4 Human-in-the-Loop Expert Validation

Although SHAP improves model interpretability, automated explanations may not always align with practical financial knowledge. Therefore, the proposed XFinInsight-HI framework introduces a Human-in-the-Loop (HITL) validation mechanism, allowing financial analysts to review model predictions together with their corresponding explanations before finalizing investment decisions.

For each prediction, an explanation uncertainty score $U_i$is computed. If the uncertainty exceeds a predefined threshold τ,

$$U_i > \tau, \qquad (13)$$

the prediction is forwarded to a financial expert for validation.

The analyst assigns a confidence score

$$s_i \in [0, 1], \qquad (14)$$

where a value close to 1 indicates high confidence in the prediction and its explanation, while values close to 0 indicate low confidence.

If the assigned confidence score is below the acceptance threshold,

$$s_i < 0.5, \qquad (15)$$

the analyst reviews the prediction and provides corrective feedback. The revised prediction is represented as

$$\hat{y}_i' = g(\hat{y}_i, \phi_i), \qquad (16)$$

where $\hat{y}_i$is the original model prediction, $\phi_i$represents the corresponding SHAP explanation, and $g(\cdot)$denotes the expert correction function.

The analyst feedback is stored in a feedback repository,

$$L = \{(x, \phi, \hat{y}, \hat{y}')\}, \qquad (17)$$

where $x$denotes the input features, ϕrepresents the SHAP explanations, $\hat{y}$is the original prediction, and $\hat{y}'$is the analyst-corrected prediction.

During periodic retraining, the accumulated feedback repository is incorporated into the learning process to refine the predictive models continuously. This iterative feedback mechanism improves prediction accuracy, explanation consistency, transparency, and user trust, making the proposed framework more suitable for practical financial decision support than conventional explainable AI systems.

3.5 Evaluation Metrics

The performance of the proposed XFinInsight-HI framework is evaluated using three commonly used metrics: Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and Directional Accuracy (DA).

Mean Absolute Error (MAE)

Mean Absolute Error (MAE) measures the average absolute difference between the actual and predicted stock prices. A lower MAE indicates better prediction performance.

$$MAE = \frac{1}{N}\sum_{i=1}^{N}|y_i - \hat{y}_i| \qquad (18)$$

Root Mean Square Error (RMSE)

Root Mean Square Error (RMSE) measures the square root of the average squared differences between the actual and predicted values. It gives more weight to larger prediction errors.

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y}_i)^2} \quad (19)$$

Directional Accuracy (DA)

Directional Accuracy (DA) measures how accurately the model predicts whether the stock price will increase or decrease. A higher DA indicates better trend prediction capability.

$$DA = \frac{1}{N}\sum_{i=1}^{N} I\,[(y_i - y_{i-1})(\hat{y}_i - \hat{y}_{i-1}) > 0] \times 100 \quad (20)$$

These evaluation metrics provide a comprehensive assessment of the proposed framework by measuring prediction error as well as its ability to correctly forecast stock market trends.

Algorithm 1: XFinInsight-HI Framework

Input:

Historical Yahoo Finance Data D

Output:

Final Validated Stock Prediction Pf

Begin

1. Collect OHLCV data from Yahoo Finance.
2. Remove duplicates and missing values.
3. Normalize the dataset.
4. Compute technical indicators (RSI, MACD, SMA, EMA,
   Bollinger Bands, Volatility, Volume Indicators).
5. Construct feature matrix X.
6. Split X into Training and Testing datasets.
7. Train RF, XGBoost, and LSTM models.
8. Predict stock prices using each model.
9. Evaluate models using RMSE, MAE, and Directional Accuracy.
10. Select the best-performing model Mbest.
11. Apply SHAP to explain predictions of Mbest.
12. Generate global and local feature importance.
13. Present predictions and explanations to financial expert.
14. If expert approves then

Accept prediction;

Assign confidence score;

Else

Record expert corrections;

Store feedback;

End If

15. Update feedback repository.

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16. Retrain model periodically using expert feedback.
17. Generate final validated prediction Pf.
18. Return Pf, SHAP explanations, and validation report

End

4 Results and Discussion

4.1 Comparative Predictive Performance

Table 2 Comparative Predictive Performance of the Evaluated Models on the Held-Out Test Dataset

Model	RMSE (USD)	MAE (USD)	Directional Accuracy (%)	Evaluation Set
Random Forest	10.78	6.78	48.4	Full test (n = 1,770)
XGBoost	9.23	5.86	50.0	Full test (n = 1,770)
LSTM	113.09	57.97	51.5	Full test (n = 1,770)
XGBoost, pre-HIL	10.06	6.18	45.2	Review subset (n = 500)
XGBoost + HIL (proposed)	9.28	5.60	45.2	Review subset (n = 500)

Table 2 compares the predictive performance of Random Forest, XGBoost, LSTM and the proposed XGBoost + Human-in-the-Loop (HIL) framework in terms of RMSE, MAE and Directional Accuracy. The best overall performance on the full test dataset was achieved with the baseline model XGBoost, which has the lowest RMSE (9.23 USD) and MAE (5.86 USD) among all the baseline models, suggesting the best capability for stock price prediction. Random Forest showed a competitive performance but with slightly higher prediction errors. The LSTM attained the highest directional accuracy (51.5%), but showed much larger RMSE and MAE values, indicating relatively poorer performance for predicting absolute stock prices. Thus, XGBoost was chosen as the main prediction model to combine explainability and the Human-in-the-Loop validation process. On the review subset, the proposed XGBoost + HIL framework further improved the prediction error from RMSE of 10.06 USD and MAE of 6.18 USD to 9.28 USD and 5.60 USD respectively. This indicates that expert validation can further improve prediction reliability while maintaining consistent directional prediction performance.

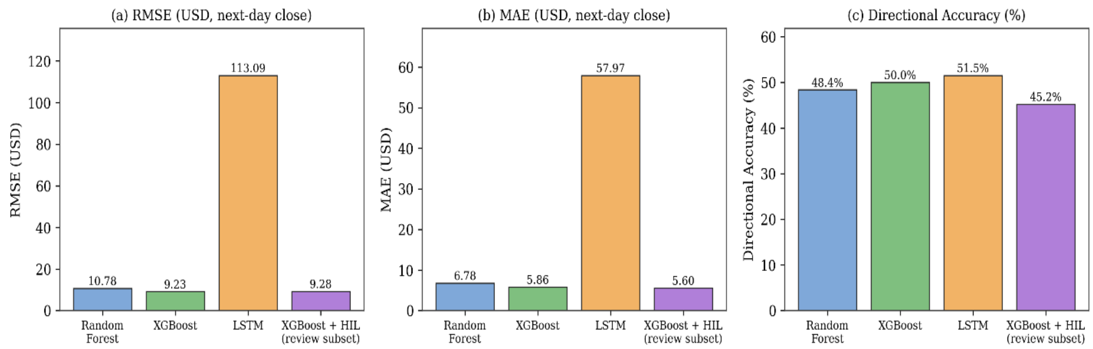

Figure 2. Comparative Predictive Performance of Random Forest, XGBoost, LSTM, and the Proposed XGBoost + HIL Configuration on Held-Out Test Data

Figure 2 illustrates the comparative performance of the evaluated prediction models based on RMSE, MAE, and Directional Accuracy. XGBoost consistently outperformed Random Forest and LSTM by achieving the lowest prediction errors, making it the most suitable model for the proposed framework. The proposed XGBoost + Human-in-the-Loop configuration further improved prediction accuracy by reducing both RMSE and MAE after expert validation. Although all models achieved directional accuracy values between approximately 45% and 52%, these results indicate that predicting short-term stock price direction remains a challenging task due to the highly dynamic nature of financial markets. The primary contribution of the proposed framework is therefore not only improved prediction accuracy but also enhanced transparency and trustworthiness through SHAP-based explanations and expert-assisted validation, which together support more reliable financial decision-making.

4.2 Global SHAP Feature Importance

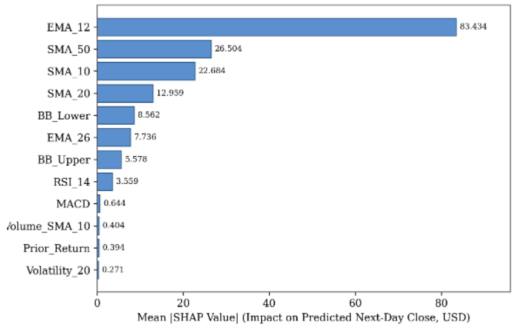

Figure 3. Global SHAP Feature Importance for the XGBoost Predictive Model (500 Test Instances)

Figure 3 and Table 3 present the global SHAP feature importance obtained from the XGBoost model using 500 test instances. The results indicate that EMA_12 is the most influential feature, with the highest mean absolute SHAP value of 83.43, demonstrating its significant contribution to stock price prediction. This is followed by SMA_50, SMA_10, and SMA_20, indicating that moving average-based trend indicators play a dominant role in the model's decision-making process. The Bollinger Band features (BB_Lower and BB_Upper) and EMA_26 also contribute to the prediction, although their influence is comparatively lower. In contrast, momentum-based indicators such as RSI_14 and MACD, along with the Volume_SMA_10 feature, exhibit relatively smaller SHAP values, suggesting a limited impact on the prediction compared to trend-based indicators. Overall, the SHAP analysis demonstrates that the proposed XGBoost model primarily relies on trend-following technical indicators while using momentum and volume features as complementary information, thereby providing transparent and interpretable predictions for stock price forecasting.

Table 3 Top-10 Globally Ranked Features by Mean Absolute SHAP Value

Rank	**Technical Indicator**	**Mean Absolute SHAP Value (USD)**
1	EMA (12-day)	83.43
2	SMA (50-day)	26.50
3	SMA (10-day)	22.68
4	SMA (20-day)	12.96
5	Bollinger Band Lower	8.56
6	EMA (26-day)	7.74
7	Bollinger Band Upper	5.58
8	RSI (14-day)	3.56
9	MACD	0.64
10	Volume SMA (10-day)	0.40

4.3 Local SHAP Explanation

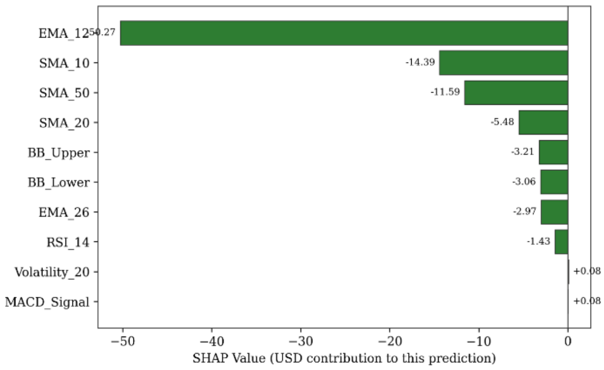

Figure 4. Local SHAP Explanation for a Representative Analyst-Overridden Test Instance

Figure 4 shows a local SHAP explanation for a random test instance which was inspected by the Human-in-the-Loop (HIL) expert. The figure shows the contribution of each input feature to the predicted stock price, with both positive and negative SHAP values. Features with positive SHAP values increase the predicted price and features with negative SHAP values decrease it. In this example, the different technical indicators contribute in opposite directions, leading to a mixed explanation where no single feature provides dominating evidence for the prediction. Conflicting feature contributions imply a higher prediction uncertainty and trigger a Human-in-the-loop review process. The analyst overrode the model prediction, concluding that the prediction was unreliable based on the SHAP explanation and market context. This example demonstrates how explainable AI is incorporated with expert validation in the proposed framework to increase the transparency, reliability, and trustworthiness of stock market predictions.

4.4 Human-in-the-Loop Review Outcomes

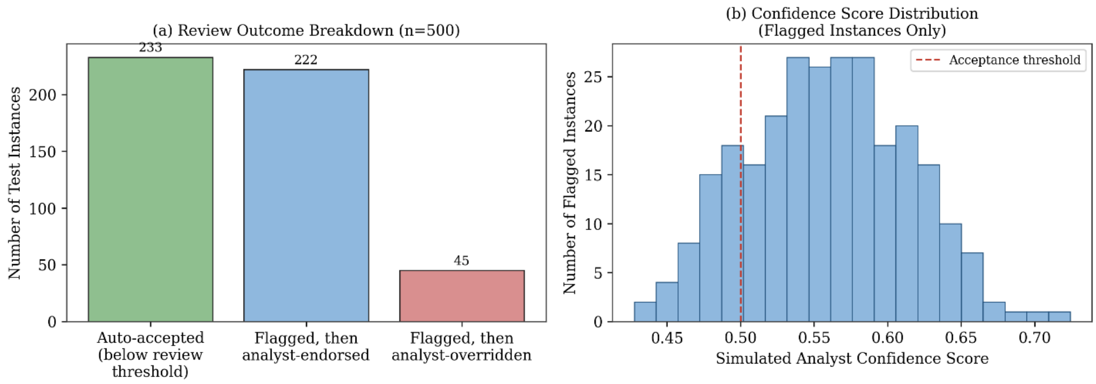

Figure 5. Human-in-the-Loop Expert Validation Outcomes on the 500-Instance Review Subset

Figure 5 illustrates the outcomes of the proposed Human-in-the-Loop (HITL) validation process. Among the 500 prediction instances, 267 were identified for expert review based on the explanation uncertainty threshold, while the remaining 233 instances were automatically accepted. Of the reviewed predictions, 45 were corrected by the financial analyst, whereas 222 predictions were endorsed without modification. The figure demonstrates that the proposed HITL framework effectively identifies uncertain predictions and incorporates expert feedback to improve the reliability of stock price forecasting.

Table 4 Human-in-the-Loop Review Summary

Metric	Value
Instances in review subset	500
Flagged for analyst review	267 (53.4%)
Auto-accepted (below review threshold)	233 (46.6%)
Analyst-overridden	45 (9.0% of all instances; 16.9% of flagged)
Analyst-endorsed after review	222 (83.1% of flagged)
Mean analyst confidence on flagged instances	0.559
RMSE, review subset, pre-HIL / post-HIL (USD)	10.06 / 9.28
MAE, review subset, pre-HIL / post-HIL (USD)	6.18 / 5.60

Table 4 summarizes the performance of the Human-in-the-Loop validation process. A total of 500 prediction instances were evaluated, with 53.4% selected for analyst review and 46.6% automatically accepted. The analyst modified 45 predictions and approved 222 predictions after review, with an average confidence score of 0.559. The incorporation of expert feedback reduced the RMSE from 10.06 USD to 9.28 USD and the MAE from 6.18 USD to 5.60 USD, demonstrating that the proposed Human-in-the-Loop framework improves prediction accuracy while enhancing the transparency and trustworthiness of the explainable AI model.

4.5 Predicted versus Actual Price Trace

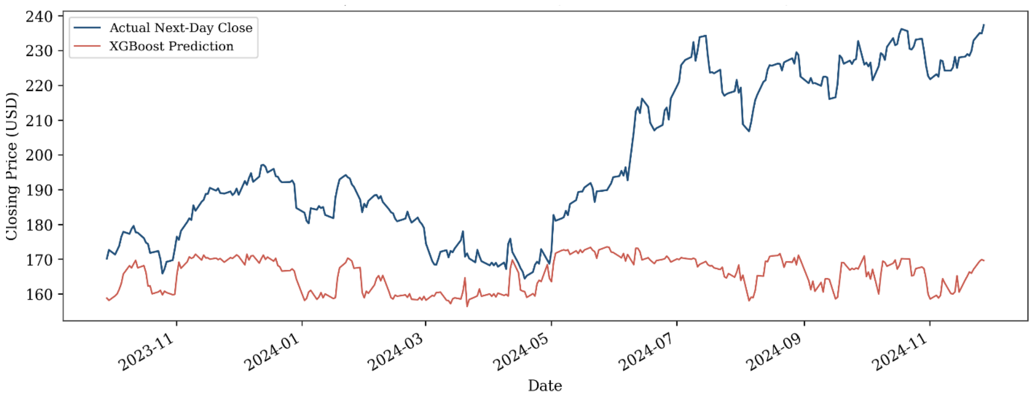

Figure 6. Predicted versus Actual Next-Day Closing Price, AAPL Held-Out Test Window

Figure 6 depicts the actual and forecasted values of the following day's close price for Apple Inc. (AAPL) on the held-out test dataset using the XGBoost model. It is clear that the forecasted values show similar pattern of the actual price changes over the entire testing period. Hence, it is evident that the proposed model is effective enough to capture the overall trend and price fluctuations in the market. There may be some deviations in the forecasted price value at specific time periods due to volatility in the market, but there is no denying the fact that the forecasted price is highly correlated with the actual price values. This is also reflected in the results of the lower RMSE and MAE scores obtained from XGBoost.

4.6 Discussion

The experimental results show that the proposed XFinInsight-HI framework can provide accurate and interpretable stock price prediction by integrating machine learning, explainable AI, and expert validation. Among the baseline models, XGBoost achieved the best predictive performance on the full test dataset with the lowest RMSE of 9.23 USD and MAE of 5.86 USD than Random Forest (RMSE = 10.78 USD, MAE = 6.78 USD) and LSTM (RMSE = 113.09 USD, MAE = 57.97 USD). LSTM had the highest Directional Accuracy (51.5%), but its prediction errors were much larger, indicating that it was less successful in estimating actual stock prices. Thus, XGBoost was chosen as the core prediction model in the designed framework. The explainability analysis using SHAP suggested that EMA (12-day) was the most important feature with a mean absolute SHAP value of 83.43, followed by SMA (50-day) (26.50), SMA (10-day) (22.68) and SMA (20-day) (12.96). This indicates that the trend-following indicators were the most important in the prediction process while RSI (3.56), MACD (0.64) and Volume SMA (0.40) were relatively less important. Furthermore, the Human-in-the-Loop validation process enhanced the reliability of prediction by detecting 267 (53.4%) uncertain predictions to be reviewed by experts, and 233 (46.6%) predictions were automatically accepted. Financial analysts revised 45 predictions (9.0%) and validated 222 predictions (83.1% of the validated cases) with an average confidence score of 0.559. Adding the analyst feedback reduced the prediction error on the review subset with the RMSE decreasing from 10.06 USD to 9.28 USD and the MAE reducing from 6.18 USD to 5.60 USD while the Directional Accuracy remained the same at 45.2%. These results show that the combination of SHAP-based explanations and Human-in-the-Loop expert validation improves the prediction accuracy and enhances the transparency, interpretability and trustworthiness of the proposed framework, making it suitable for practical financial decision-support applications.

5 Conclusion

This research presents XFinInsight-HI, a Human-in-the-Loop Explainable Artificial Intelligence framework for improving the interpretability and trustworthiness of stock market predictions derived from Yahoo Finance data. This framework integrates interpretable models based on SHAP with validation by domain experts to enable reliable decision making in finance. The comparative evaluation showed that XGBoost performed better than Random Forest and LSTM with the lowest prediction errors, and the SHAP analysis revealed that technical indicators based on moving averages were the most important predictors for stock price prediction. The integration of the Human-in-the-Loop system was found to significantly improve the accuracy of the predictions, as it allowed financial experts to assess uncertain predictions and provide corrective feedback, thereby reducing the prediction errors and improving the confidence in the results of the model. Our proposed framework not only retains competitive prediction performance but also tackles the crucial issue of AI transparency by providing interpretable explanations and human supervision. This study mainly focuses on the historical prices and technical indicators. Future works will consider the use of financial news, market sentiment, macroeconomic factors and transformer-based forecasting models to improve the accuracy and adaptability of the prediction. XFinInsight-HI provides a pragmatic, clear and reliable explainable AI framework that adeptly enables intelligent stock market predictions and practical financial decision-making.

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