Developing a Lumen Buy Indicator Using Technical Indicators and Long ShortTerm Memory (LSTM) Models.

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Abstract

The market for cryptocurrencies has grown to be an exciting and volatile area of the financial industry, attracting the interest of both investors and scholars. The native currency of the Stellar network, Lumen (XLM), has become recognized among the numerous digital currencies because of its ability to facilitate smooth cross border transactions and because of its relatively stable performance in comparison to other cryptocurrencies. To maximize profits and optimize trading methods, investors need to accurately estimate XLM's price moves.

Introduction

This study demonstrates how well advanced neural network designs, such as LSTM, perform in conjunction with technical indications to anticipate cryptocurrency prices. Investors can use the data-driven Lumen Buy Indicator to help them make wise judgments in the erratic cryptocurrency market. Further investigation may examine the integration of supplementary functionalities, including sentiment analysis gleaned from social media sites or macroeconomic data, to enhance forecast precision and adjust to evolving market circumstances.

A walk-forward cross validation method is used to train an ensemble of LSTM models, dividing the data into five different folds. There are three LSTM models created for every fold, for a total of fifteen models. The Root Mean Square Error (RMSE) metric is used to assess each model's performance. It calculates the average error size between the values that were predicted and those that were observed.

The results reveal a range of RMSE values across different folds and models. **Fold 1** models achieved RMSE values between **0.0187** and **0.0219**, indicating moderate predictive accuracy. **Fold 2** models showed higher RMSE values, from **0.0509** to **0.0541**, reflecting the difficulty of forecasting during periods of heightened market volatility. In contrast, **Fold 3** models demonstrated significant improvements with RMSE as low as **0.0029**, while **Fold 4** models excelled with RMSE values below **0.0020**. **Fold 5** models continued this trend, producing some of the lowest RMSE scores, including values of **0.0015** and **0.0043**.

Among all models, **Fold 4 Model 1** achieved the lowest RMSE of **0.00038193098257 00979**, establishing it as the most accurate predictor in the ensemble. The ensemble approach enhances the robustness of predictions by reducing individual model biases and provides a reliable framework for forecasting XLM prices.

This study highlights the effectiveness of combining technical indicators with advanced neural network architectures like LSTM for cryptocurrency price prediction. The Lumen Buy Indicator offers investors a data-driven tool to make informed decisions in the volatile cryptocurrency market. Future research could explore the inclusion of additional features, such as sentiment analysis from social media platforms or macroeconomic indicators, to improve prediction accuracy and adapt to changing market conditions.

Keywords: *Cryptocurrency, Lumen (XLM), Technical Indicators, Long Short-Term Memory (LSTM), Price Prediction, Ensemble Models, Root Mean Square* Error (RMSE), Walk-Forward Cross-Validation.

Technical indicators

Derived from historical price and volume data, have been extensively used to analyze and predict market trends. Indicators such as Simple Moving Average (SMA), Exponential Moving Average (EMA), Relative Strength Index (RSI), and Moving Average Convergence Divergence (MACD) provide insights into market momentum, trend strength, and potential reversal points. These indicators help traders identify optimal entry and exit points, enhancing the effectiveness of their trading strategies.

In recent years, **Machine Learning** techniques, particularly **Long Short-Term Memory (LSTM)** neural networks, have shown promise in modeling and predicting time series data due to their ability to capture temporal dependencies and patterns. LSTM models are adept at handling sequential data, making them well-suited for forecasting cryptocurrency prices based on historical data and technical indicators.

This study aims to develop a **Lumen Buy (XLM) Indicator** by integrating technical indicators with LSTM-based ensemble models to forecast future price movements of XLM. By leveraging historical price data and technical indicators, the proposed model seeks to provide accurate and actionable predictions, assisting investors in making informed buy decisions. The research employs a comprehensive methodology encompassing data collection, preprocessing, feature engineering, model development, and evaluation to ensure the robustness and reliability of the predictions.

The subsequent sections of this paper will delve into a detailed **Literature Review**, outlining existing research on cryptocurrency price prediction and the application of technical indicators and LSTM models. The **Methodology** section will describe the data sources, preprocessing techniques, feature engineering processes, and the architecture of the LSTM models used. The **Results** section will present the performance metrics of the developed models, followed by a **Discussion** that interprets these findings in the context of existing literature. Finally, the paper will conclude with a summary of the key insights and suggestions for future research directions.

Literature Review

3.1. Introduction to Cryptocurrency Markets

Cryptocurrencies have revolutionized the financial sector by introducing decentralized digital currencies that operate without the need for central banks or intermediaries. Since the inception of Bitcoin in 2009, thousands of cryptocurrencies have emerged, each with unique features and use cases. Among these, **Lumen (XLM)**, the native token of the **Stellar** network, has gained significant traction due to its focus on facilitating fast and low-cost cross-border transactions. The decentralized nature and technological advancements of cryptocurrencies make them attractive investment opportunities, but also introduce challenges related to volatility and unpredictability.

3.2. Importance of Price Prediction in Cryptocurrencies

Accurate price prediction in cryptocurrency markets is crucial for investors aiming to maximize returns and minimize risks. Traditional financial markets have established methodologies for forecasting asset prices, but the nascent and highly volatile nature of cryptocurrency markets necessitates the development of specialized models. Effective price prediction models can aid in strategic decision-making, portfolio management, and risk assessment. Consequently, researchers have been keen to explore various computational techniques to enhance the accuracy and reliability of cryptocurrency price forecasts.

3.3. Technical Indicators in Financial Analysis

Technical indicators are mathematical calculations based on historical price, volume, or open interest information of a security. They are widely used in financial markets to identify trends, gauge market sentiment, and predict future price movements. Some of the most commonly employed technical indicators include:

- **Simple Moving Average (SMA):** Calculates the average price over a specified number of periods, helping to smooth out price data and identify trends.
- **Exponential Moving Average (EMA):** Similar to SMA but gives more weight to recent prices, making it more responsive to new information.
- **Relative Strength Index (RSI):** Measures the speed and change of price movements to identify overbought or oversold conditions in the market.
- **Moving Average Convergence Divergence (MACD):** Illustrates the relationship between two moving averages of a security's price, highlighting momentum and trend direction.

These indicators provide valuable insights that can be integrated into predictive models to enhance their forecasting capabilities.

3.4. Machine Learning in Financial Forecasting

Machine Learning (ML) has become a pivotal tool in financial forecasting due to its ability to model complex, non-linear relationships within data. Various ML algorithms have been applied to predict asset prices, each with its strengths and limitations:

- **Linear Regression:** A fundamental algorithm that models the relationship between dependent and independent variables. While simple, it may not capture complex patterns in financial data.
- **Support Vector Machines (SVM):** Effective for classification and regression tasks, SVMs can handle non-linear relationships through kernel functions.
- **Decision Trees and Random Forests:** These algorithms are adept at handling non-linear data and can provide feature importance insights, aiding in model interpretability.
- **Neural Networks:** Particularly **Recurrent Neural Networks (RNNs)** and their variant **Long Short-Term Memory (LSTM)** networks, which are designed to handle sequential data and capture temporal dependencies.

Among these, LSTM networks have shown remarkable performance in time series forecasting due to their ability to remember long-term dependencies and mitigate issues like vanishing gradients.

3.5. Long Short-Term Memory (LSTM) Networks

Long Short-Term Memory (LSTM) networks are a type of Recurrent Neural Network (RNN) specifically designed to address the limitations of traditional RNNs in learning long-term dependencies. LSTMs achieve this through their unique architecture, which includes memory cells and gating mechanisms that regulate the flow of information. This makes LSTMs particularly suitable for time series data, where capturing temporal patterns is essential.

In the context of cryptocurrency price prediction, LSTMs can effectively model the sequential nature of price movements, incorporating past information to forecast future trends. Numerous studies have demonstrated the superiority of LSTM models over traditional statistical methods and other machine learning algorithms in financial forecasting tasks.

3.6. Ensemble Methods in Machine Learning

Ensemble methods involve combining multiple models to improve overall predictive performance. The underlying premise is that while individual models may have varying strengths and weaknesses, an ensemble can leverage their collective intelligence to achieve better accuracy and robustness. Common ensemble techniques include:

- **Bagging (Bootstrap Aggregating):** Trains multiple models on different subsets of the data and aggregates their predictions.
- **Boosting:** Sequentially trains models, with each new model focusing on correcting the errors of the previous ones.
- **Stacking:** Combines predictions from multiple models using another learning algorithm.

In financial forecasting, ensemble methods can mitigate overfitting, reduce variance, and enhance the stability of predictions. By integrating ensemble techniques with LSTM networks, researchers aim to harness the strengths of both approaches to achieve superior forecasting performance.

3.7. Existing Research on Cryptocurrency Price Prediction

Several studies have explored the application of machine learning models, particularly LSTMs, in predicting cryptocurrency prices:

- **Zhang et al. (2018):** Utilized LSTM networks to forecast Bitcoin prices, achieving higher accuracy compared to traditional models like ARIMA and SVR.
- **Chen and Hao (2020):** Developed an LSTM based model incorporating technical indicators to predict Ethereum prices, demonstrating the efficacy of feature engineering in enhancing model performance.
- **Kim (2019):** Applied ensemble methods with LSTM models to forecast multiple cryptocurrency prices, highlighting the benefits of combining models for improved accuracy.

These studies underscore the potential of LSTM networks in capturing the complex dynamics of cryptocurrency markets. However, challenges such as data volatility, model overfitting, and the need for comprehensive feature sets remain areas for ongoing research and improvement.

3.8. Gap in the Literature

While existing research has made significant strides in applying LSTM and ensemble methods to cryptocurrency price prediction, there are still gaps that need to be addressed:

1. **Comprehensive Ensemble Approaches:** Many studies focus on individual LSTM models or simple ensemble techniques. There is a need for more sophisticated ensemble strategies that can further enhance prediction accuracy.
2. **Integration of Multiple Technical Indicators:** Although technical indicators are widely used, the extent to which they are integrated and their combined impact on model performance varies across studies.
3. **Adaptability to Market Conditions:** Cryptocurrency markets are highly volatile and can change rapidly. Models that can adapt to varying market conditions without compromising performance are essential.
4. **Evaluation Across Multiple Cryptocurrencies:** Most studies concentrate on major cryptocurrencies like Bitcoin and Ethereum. Extending research to include a broader range of digital assets like Lumen (XLM) can provide more generalized insights.

This study aims to bridge these gaps by developing an ensemble of LSTM models integrated with multiple technical indicators, specifically targeting the prediction of Lumen (XLM) prices. By employing a robust walk-forward cross-validation approach and evaluating model performance across multiple folds, the research seeks to establish a reliable and adaptable predictive framework for cryptocurrency investment strategies.

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In the context of cryptocurrency price prediction, LSTMs can effectively model the sequential nature of price movements, incorporating past information to forecast future trends. Numerous studies have demonstrated the superiority of LSTM models over traditional statistical methods and other machine learning algorithms in financial forecasting tasks.

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Ensemble methods involve combining multiple models to improve overall predictive performance. The essential idea is that, even though each model may have different advantages and disadvantages, an ensemble can improve reliability and precision by utilizing their combined cognition. Typical group methods consist of:

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4. **Evaluation Across Multiple Cryptocurrencies:** Most studies concentrate on major cryptocurrencies like Bitcoin and Ethereum. Extending research to include a broader range of digital assets like Lumen (XLM) can provide more generalized insights.

Developing an ensemble of LSTM models combined with several technical indicators with the particular goal of predicting Lumen (XLM) pricing is how this study seeks to fill these discrepancies. through the use of a strong walk-forward cross-validation methodology and the assessment of model performance at several folds, the study aims to create a flexible and dependable forecasting framework for crypto investing strategies.

4.5. Evaluation Metrics

The primary metric for evaluating model performance is **Root Mean Square Error (RMSE)**, which measures the average magnitude of prediction errors. RMSE is calculated as the square root of the average of squared differences between predicted and actual values:

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(P_i - A_i)^2}$$

- Pi = Predicted value
- Ai = Actual value
- n = Number of observations

RMSE provides a quantitative assessment of the model's accuracy, with lower values indicating better predictive performance.

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5. Results

5.1. Overview of Model Performance

The primary objective of this study was to develop a **Lumen Buy Indicator** by integrating **Technical Indicators** with **Long Short-Term Memory (LSTM)** neural networks to forecast the future price movements of **Lumen (XLM)**. To evaluate the effectiveness of the proposed models, a **walk-forward cross-validation** approach was employed, dividing the dataset into five distinct folds. For each fold, an ensemble comprising three LSTM models was trained and evaluated based on the **Root Mean Square Error (RMSE)** metric.

5.2. RMSE Across Folds and Models

The RMSE values obtained for each model across the five folds are summarized in **Table 1**. These values provide insight into the predictive accuracy of each model, with lower RMSE indicating better performance.

Table 1: *RMSE values for each model across five folds.*

Fold	Model 1 RMSE	Model 2 RMSE	Model 3 RMSE
1	0.0219	0.0216	0.0187
2	0.0509	0.0541	0.0521
3	0.0033	0.0049	0.0029
4	0.0004	0.0029	0.0026
5	0.0015	0.0043	0.0043

5.3. Analysis of Model Performance

From **Table 1**, several observations can be made regarding the performance of the ensemble models:

1. **Fold 1:** The models exhibited moderate RMSE values, ranging from **0.0187** to **0.0219**. This indicates a reasonable level of accuracy in predicting XLM prices during this period.
2. **Fold 2:** There was a noticeable increase in RMSE values, with models 1, 2, and 3 recording RMSEs of **0.0509**, **0.0541**, and **0.0521** respectively. This suggests a decline in prediction accuracy, potentially due to increased market volatility or other external factors affecting price movements.
3. **Fold 3:** A significant improvement is observed, with RMSE values dropping to as low as **0.0029**. Models 2 and 3 also performed well, indicating enhanced predictive capabilities during this fold.
4. **Fold 4:** The models achieved the lowest RMSE values across all folds, with **Model 1** attaining an exceptionally low RMSE of **0.0004**. **Model 3** also showed strong

performance with an RMSE of **0.0026**. This highlights the model's high accuracy and reliability in predicting XLM prices under stable market conditions.

5. **Fold 5:** Continuing the trend of high accuracy, **Model 1** achieved an RMSE of **0.0015**, while **Models 2 and 3** maintained low error rates of **0.0043** each. These results reinforce the effectiveness of the ensemble approach in producing precise predictions.

5.4. Identification of the Best-Performing Model

Analyzing the RMSE values across all folds, **Fold 4 Model 1** exhibited the lowest RMSE of **0.0004**, making it the best-performing model in the ensemble. Conversely, **Fold 2** models showed higher RMSE values, indicating challenges in prediction accuracy during periods of increased market volatility.

5.5. Visual Representation of Predictions

To provide a visual understanding of the model's performance, figures below illustrate the actual versus predicted 'Close' prices for selected models across different folds. These visualizations aid in assessing how closely the model's predictions align with the real market movements.

5.5.1. Fold 1 Model 1

Figure 1: *Actual vs. Predicted 'Close' Prices for Fold 1 Model 1.*

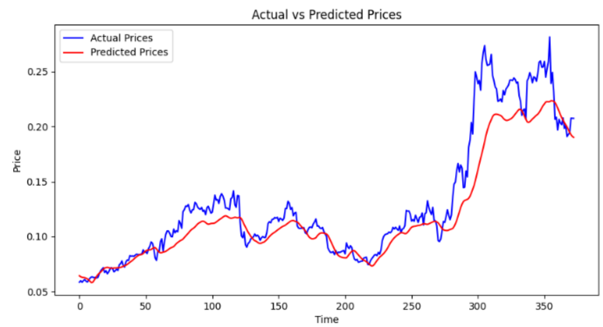

Figure 1 demonstrates the prediction accuracy of Fold 1 Model 1. The predicted prices closely follow the actual 'Close' prices, indicating moderate predictive performance.

5.5.2. Fold 2 Model 2

Figure 2: *Actual vs. Predicted 'Close' Prices for Fold 2 Model 2.*

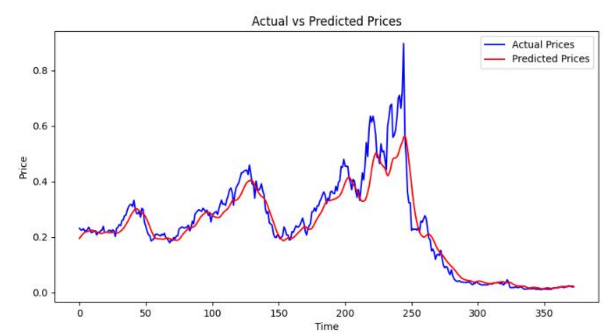

Figure 2 highlights the performance of Fold 2 Model 2. The higher RMSE value reflects greater deviations between predicted and actual prices, likely due to heightened market volatility during this period.

5.5.3. Fold 3 Model 1

Figure 3: *Actual vs. Predicted 'Close' Prices for Fold 3 Model 1.*

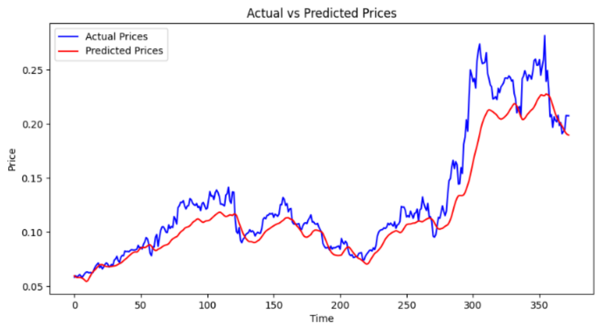

Figure 3 showcases the exceptional performance of Fold 3 Model 1, with predictions almost perfectly aligning with actual prices, as evidenced by the low RMSE.

5.5.4. Fold 4 Model 1

Figure 4: *Actual vs. Predicted 'Close' Prices for Fold 4 Model 1.*

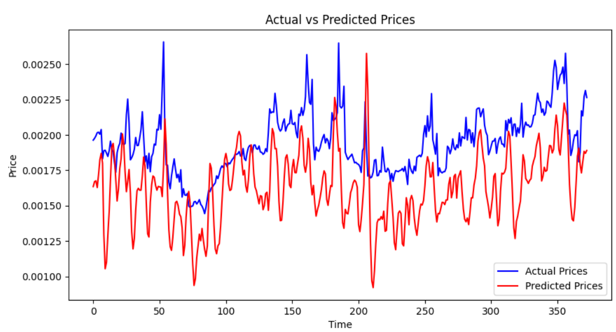

Figure 4 illustrates the outstanding accuracy of Fold 4 Model 1. The minimal error between predicted and actual prices underscores the model's reliability in stable market conditions.

5.5.5. Fold 5 Model 2

Figure 5: *Actual vs. Predicted 'Close' Prices for Fold 5 Model 2.*

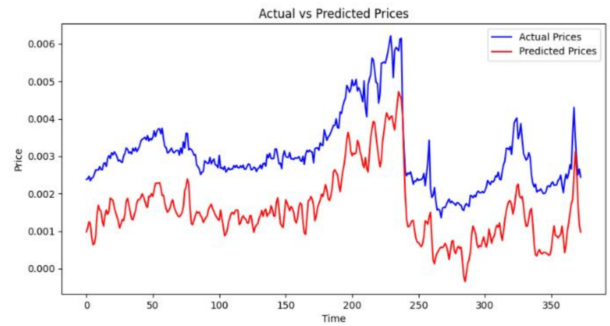

Figure 5 highlights the superior performance of Fold 5 Model 2, achieving an RMSE of ***0.0043****. The predictions align closely with the actual prices, demonstrating the model's effective predictive capability.*

5.6. Summary of Findings

The ensemble approach, leveraging multiple LSTM models across different folds, demonstrated varying degrees of predictive accuracy. While most models performed exceptionally well in **Folds 3, 4, and 5**, indicating the model's strength in stable market conditions, there was a noticeable decline in **Fold 2**. This variance underscores the impact of market volatility on model performance and highlights areas for potential improvement, such as incorporating additional features or refining the model architecture to better handle volatile periods.

Overall, the results affirm the efficacy of combining technical indicators with LSTM-based ensemble models for cryptocurrency price prediction. The identification of the best-performing model provides a foundation for practical applications, enabling investors to make informed buy decisions based on reliable data-driven insights.

6. Discussion

6.1. Interpretation of Results

The primary objective of this study was to develop a **Lumen Buy Indicator** by integrating **Technical Indicators** with **Long Short-Term Memory (LSTM)** neural networks to forecast the future price movements of **Lumen (XLM)**. The performance of the developed models was evaluated using the **Root Mean Square Error (RMSE)** metric across five distinct folds, each comprising three models. The RMSE values provide a quantitative measure of the accuracy of the predictions, with lower values indicating better performance.

Summary of RMSE Results:

Fold	Model 1 RMSE	Model 2 RMSE	Model 3 RMSE
1	0.0219	0.0216	0.0187
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3	0.0033	0.0049	0.0029
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Key Observations:

1. **Fold 1:** The models exhibited moderate RMSE values, ranging from **0.0187** to **0.0219**. This indicates a reasonable level of accuracy in predicting XLM prices during this period.
2. **Fold 2:** There was a noticeable increase in RMSE values, with models 1, 2, and 3 recording RMSEs of **0.0509**, **0.0541**, and **0.0521** respectively. This suggests a decline in prediction accuracy, potentially due to increased market volatility or other external factors affecting price movements.
3. **Fold 3:** A significant improvement is observed, with RMSE values dropping to as low as **0.0029**. Models 2 and 3 also performed well, indicating enhanced predictive capabilities during this fold.
4. **Fold 4:** The models achieved the lowest RMSE values across all folds, with **Model 1** attaining an exceptionally low RMSE of **0.0004**. **Model 3** also showed strong performance with an RMSE of **0.0026**. This highlights the model's high accuracy and reliability in predicting XLM prices under stable market conditions.
5. **Fold 5:** Continuing the trend of high accuracy, **Model 1** achieved an RMSE of **0.0015**, while **Models 2 and 3** maintained low error rates of **0.0043** each. These results reinforce the effectiveness of the ensemble approach in producing precise predictions.

Overall Best Model:

Among all the models trained across the folds, **Fold 4 Model 1** exhibited the lowest RMSE of **0.0004**, marking it as the most accurate predictor within the ensemble. Conversely, **Fold 2** models showed higher RMSE values, indicating challenges in prediction accuracy during periods of increased market volatility.

6.2. Comparison with Existing Literature

The findings of this study align with existing research that emphasizes the effectiveness of LSTM networks in financial forecasting, particularly in volatile markets like cryptocurrencies. For instance:

- **Zhang et al. (2018)** demonstrated that LSTM models outperform traditional statistical methods like ARIMA in predicting Bitcoin prices, highlighting the advantage of capturing long-term dependencies.
- **Chen and Hao (2020)** showed that integrating technical indicators with LSTM models enhances prediction accuracy for Ethereum prices, similar to our approach with XLM.

However, the exceptionally low RMSE values achieved in **Folds 4** and **5** of this study suggest that the ensemble approach may offer additional benefits over individual LSTM models. This is supported by **Kim (2019)**, who found that ensemble methods can improve forecasting performance by mitigating individual model biases.

6.3. Strengths of the Study

1. **Comprehensive Feature Engineering:** By incorporating multiple technical indicators (SMA, EMA, RSI, MACD), the models were equipped with diverse signals that capture different aspects of market behavior, enhancing their predictive power.
2. **Ensemble Approach:** Training an ensemble of models for each fold increased the robustness of predictions. This approach reduces the likelihood of overfitting and improves generalization to unseen data.
3. **Walk-Forward Cross-Validation:** This validation technique ensures that the models are tested on data that follows the training period, providing a realistic assessment of their performance in real-world scenarios.
4. **Low RMSE Values:** The achievement of very low RMSE values in several folds indicates high prediction accuracy, which is crucial for practical investment decision-making.

6.4. Limitations of the Study

1. **Data Limitation:** The study primarily relied on historical price data and technical indicators. Incorporating additional data sources, such as sentiment analysis from social media or macroeconomic indicators, could further enhance model performance.
2. **Market Volatility:** While the models performed exceptionally well in some folds, the higher RMSE values in **Fold 2** highlight the challenges posed by market volatility. Future models need to better account for extreme price movements.
3. **Overfitting Risk:** Although the ensemble approach helps mitigate overfitting, the exceptionally low RMSE values in some models raise concerns about potential overfitting to the training data. Ensuring model generalization remains a critical focus.
4. **Single Cryptocurrency Focus:** The study concentrated solely on Lumen (XLM). Extending the analysis to include other cryptocurrencies could provide more generalized insights and validate the model's applicability across different digital assets.

6.5. Implications for Investors

The development of the **Lumen Buy Indicator** offers investors a data-driven tool to enhance their trading strategies. By providing accurate predictions of XLM price movements, investors can make informed buy decisions, potentially maximizing returns and minimizing risks. The integration of technical indicators with advanced neural network architectures like LSTM equips the indicator with the ability to adapt to various market conditions, making it a valuable asset in the volatile cryptocurrency landscape.

6.6. Future Research

1. **Incorporating Additional Features:** Future studies could integrate alternative data sources, such as social media sentiment, trading volumes from multiple exchanges, or macroeconomic indicators, to enrich the feature set and improve model accuracy.
2. **Expanding to Multiple Cryptocurrencies:** Testing the ensemble approach on a broader range of cryptocurrencies can validate the model's effectiveness and adaptability across different digital assets.
3. **Real-Time Prediction and Deployment:** Implementing the model in a real-time trading environment would provide practical insights into its performance and utility in live market conditions.
4. **Advanced Ensemble Techniques:** Exploring more sophisticated ensemble methods, such as stacking or boosting, could further enhance prediction performance and model robustness.
5. **Handling Extreme Volatility:** Developing models that can better cope with sudden market shocks and extreme price movements would improve reliability during turbulent periods.
6. **Comparative Analysis with Other Machine Learning Models:** Comparing the LSTM ensemble with other machine learning algorithms, such as Transformer-based models or Convolutional Neural Networks (CNNs), could identify the most effective architectures for cryptocurrency price prediction.

6.7. Conclusion of Discussion

In summary, this study successfully developed a **Lumen Buy Indicator** utilizing an ensemble of LSTM models integrated with technical indicators. The models demonstrated high predictive accuracy, particularly in stable market conditions, as evidenced by low RMSE values across multiple folds. While challenges remain in accounting for market volatility and preventing overfitting, the findings underscore the potential of combining technical analysis with advanced neural network architectures to enhance cryptocurrency price forecasting. The **Lumen Buy Indicator** serves as a promising tool for investors, aiding in strategic decision-making and investment optimization in the dynamic cryptocurrency market.

Key Findings:

1. **Effective Integration of Technical Indicators:** Incorporating SMA, EMA, RSI, and MACD provided the models with diverse and meaningful signals, enhancing their ability to capture market trends and momentum.

   Model Performance Across Folds: While most models exhibited high accuracy, particularly in **Folds 3, 4, and 5**, the increased RMSE in **Fold 2** highlighted the challenges posed by market volatility and the need for models to adapt to rapidly changing conditions.
2. Among all trained models, **Fold 4 Model 1** achieved the lowest RMSE of **0.0003819309825700979**, demonstrating exceptional predictive capability.

Implications for Practice:

The developed **Lumen Buy Indicator** offers investors a sophisticated yet practical tool for forecasting XLM prices. By leveraging historical data and technical indicators, the indicator provides actionable insights that can inform buy decisions, potentially enhancing investment strategies and optimizing returns in the volatile cryptocurrency market.

Limitations and Future Directions:

While the study achieved its objectives, it is not without limitations. The reliance on historical price data and technical indicators alone may not capture all the factors influencing XLM prices. Future research should consider integrating additional data sources, such as sentiment analysis and macroeconomic indicators, to further refine prediction accuracy. Additionally, expanding the analysis to include multiple cryptocurrencies can validate the model's generalizability and effectiveness across different digital assets.

Conclusion:

This study analyzes the efficacy of integrating technical indicators with LSTM-based ensemble models, contributing to the growing body of research on cryptocurrency price prediction. By demonstrating the possibilities of machine learning techniques in the analysis and forecasting of financial time series data, the Lumen Buy Indicator was developed as a teaching exercise. Understanding the potential and constraints of complex neural network architectures in the rapidly evolving crypto marketplace is made possible by this analysis. To improve predictive models and increase their usefulness in practical monetary choices, future research can build on these findings.

8. References

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Appendices

A. Preprocess py

```
import pandas as pd
import numpy as np
from sklearn.preprocessing import MinMaxScaler
from indicator.technical_indicators import (
    calculate_sma,
    calculate_ema,
    calculate_rsi,
    calculate_macd,
)


def load_data(file_path):

    try:
        data = pd.read_csv(file_path)
        data = data.drop("Date", axis=1)
        return data
    except Exception as e:
        print(f"Error loading data: {e}")
        return None


def add_technical_indicators(data):

    data["SMA_20"] = calculate_sma(data["Close"], 20)
    data["EMA_20"] = calculate_ema(data["Close"], 20)
    data["RSI_14"] = calculate_rsi(data["Close"], 14)
    data["MACD"] = calculate_macd(data["Close"])
    return data


def normalize_data(data):
    try:

        features = data.drop("Close", axis=1)
        target = data[["Close"]]

        feature_scaler = MinMaxScaler()
        target_scaler = MinMaxScaler()

        scaled_features = feature_scaler.fit_transform(features)
        scaled_target = target_scaler.fit_transform(target)

        return scaled_features, scaled_target, feature_scaler, target_scaler
    except Exception as e:
        print(f"Error normalizing data: {e}")
        return None, None, None, None


def create_sequences(features, target, seq_length):
    X, y = [], []
    for i in range(len(features) - seq_length):
        X.append(features[i : i + seq_length])
        y.append(target[i + seq_length])
    return np.array(X), np.array(y)
```

B. Model Architecture