FORECASTING DAILY BITCOIN PRICE: A COMPARATIVE STUDY OF ARIMA-GARCH LSTM HYBRID MODEL AND TEMPORAL FUSION TRANSFORMER

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1. ABSTRACT

Bitcoin has emerged as a leading cryptocurrency, yet its rapidly fluctuating and highly nonlinear price dynamics pose significant challenges for accurate forecasting. In this study, we propose a hybrid modeling approach that integrates an ARIMA-GARCH framework with Long Short-Term Memory (LSTM) neural networks to predict Bitcoin's daily price. We train and validate the models using historical Bitcoin price data, evaluating performance with Mean Absolute Error (MAE), Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and Mean Absolute Percentage Error (MAPE), and R-Squared(R^2) . Additionally, we incorporate external indicators such as sentiment, blockchain, cross-market to further refine our predictions. Experimental results demonstrate that the proposed hybrid approach enhances forecasting accuracy, offering a more robust tool for investors and researchers seeking to navigate Bitcoin's complex market behavior.

2. INTRODUCTION

Cryptocurrencies, particularly Bitcoin, have rapidly gained prominence as potential alternatives to traditional currencies. However, Bitcoin's inherent price volatility and nonlinear behavior pose significant challenges for accurate forecasting. Reliable price predictions are crucial for investors and traders to make informed decisions and mitigate risk. Historically, time series models such as Autoregressive Integrated Moving Average (ARIMA) and Generalized Autoregressive Conditional Heteroskedasticity (GARCH) have been popular choices due to their effectiveness in capturing linear trends and volatility clustering.

Over the past few years, deep learning methods—especially Long Short-Term Memory (LSTM) neural networks—have demonstrated remarkable capabilities in handling sequential data. By capturing nonlinear dependencies and long-term temporal patterns, LSTMs are well-suited for forecasting highly volatile and rapidly changing time series, like Bitcoin prices. Nonetheless, relying solely on LSTMs may overlook certain linear and volatility-specific aspects that traditional ARIMA-GARCH models handle more effectively.

In this study, we propose a hybrid model that combines ARIMA-GARCH with LSTM to enhance the accuracy of daily Bitcoin price forecasts. The ARIMA-GARCH component captures linear trends and volatility effects, while the LSTM network identifies remaining complex nonlinear relationships and long-term dependencies. Along with LSTM, we add an Temporal Fusion Transformer [1] as a new model to also learn remaining unexplained of ARIMA-GARCH model. By integrating these approaches, the hybrid model leverages the strengths of both to produce more robust and reliable predictions. We evaluated the forecast performance using Mean Squared Error (MSE), Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE), and R Squared (R^2).

The remainder of this paper is organized as follows: Section 3 reviews related work, and Section 4 outlines the methods used for Bitcoin price prediction. Section 5 presents and discusses the experimental results, while Section 6 concludes the paper and highlights potential directions for future research.

3. RELATED WORKS

Our paper is inspired by a recent study by Mardjo and Choksuchat (2024) proposed HyBiLSTM [2], a hybrid model for bitcoin price forecasting. Their approach leverages the strengths of ARIMAX-GARCHX to capture linear trends, volatility, and external factors, and they combine it with multiple variants of LSTM (i.e., standard LSTM, BiLSTM, and attention-based layer LSTM) to capture nonlinear components and bidirectional temporal patterns. They successfully demonstrated improvements over standalone models, resulting in reliable results in Bitcoin price forecasting. In addition, they used SHAP (Shapley additive explanation) to understand the exogenous factors affecting Bitcoin price forecasting. Based on the successes of the above study, we refer to and develop a hybrid model with further improvements.

4. METHODOLOGY

This section details the methodological framework adopted for forecasting short-term daily Bitcoin prices. The approach shown in Fig. 1 integrates statistical time series models with deep learning variants to capture both linear and nonlinear dependencies within the data. The general workflow comprises data collection, preprocessing using Principal Component Analysis (PCA) to reduce multicollinearity, ARIMA-GARCH modeling, LSTM variants and a Temporal Fusion Transformer model implementations. Performance is measured at each stage to evaluate the efficacy of the models.

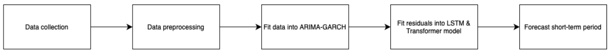

Fig. 1: Overview of the Methodology

4.1 DATA COLLECTION

The dataset comprises daily closing prices of Bitcoin along with a set of exogenous indicators that include:

- **Sentiment Indicators**: Derived from bitcoin-related search term over time.
- **Blockchain Indicators**: Metrics extracted from blockchain data (active address, hash rate, minter revenue)
- **Technical Indicators**: Computed from close price, trading volume, high, and low values (e.g., sma, ema, rsi, macd, bb, atr, volatility index)
- **Macro and Cross-Market Metrics**: economic indicators and data from related markets that may impact Bitcoin:
  - Commodities Price (Gold & Oil)
  - Traditional Equity Market (GSPC, DJI, IXIC, NYSE FANG+, ARK Innovation ETF)
  - Market Volatility & Risk Indicator (CBOE Volatility Index)
  - Global & Emerging Market (iShares MSCI Emerging Market ETF, Shanghai Composite Index)
  - Currency & Forex Dynamics (USD Index, EUR to USD Exchange rate)

The inclusion of these indicators is supported by various studies that highlight their importance in improving Bitcoin predictions:

1. Research indicates that technical indicators are significant short-run predictors of Bitcoin prices, while macroeconomic factors serve as long-term predictors. This finding underscores the relevance of both types of indicators in developing robust forecasting models. [3]
2. A study demonstrated that using a comprehensive set of technical indicators significantly improved prediction accuracy in volatile markets like cryptocurrency. The model achieved over 92% accuracy in buy/sell signal predictions. [4]
3. Research has shown that incorporating a variety of features, including sentiment analysis and technical indicators, can lead to superior performance in predicting Bitcoin prices compared to traditional methods. [5]

4.2 DATA PREPROCESSING

To prepare the data for modeling, several essential preprocessing steps were performed to ensure data quality and continuity. First, a complete date range was generated from the start to the end date of the dataset to ensure temporal continuity. Missing values were then addressed using a combination of methods: forward fill for edge cases, linear interpolation for small gaps, and ARIMA-based imputation for larger gaps. A fallback strategy, such as using the median or mean of the feature, was employed for any remaining missing values to ensure completeness. Finally, all preprocessed indicators were combined into a single, integrated dataset, with 'btc_close' prices designated as the target variable for subsequent modeling.

Next, Principal Component Analysis (PCA) was applied [6] 2 times to determine the optimal number of Principal Components with the chosen variance threshold of 95% to balance between retaining meaningful information and reducing complexity. PCA is a technique used to reduce the dimensionality of the data while retaining the most important information. Dataset is divided into three subsets: training (0.6), validation(0.2), and testing(0.2). Then, PCA is fit and transform on features in train set to extract the principal components (PCs). Finally, PCA transforms features on validation and test set. This process ensure no data leakage to the model learning and predicting process.

4.3 FORECASTING MODEL

The forecasting model consists of two main components: ARIMA-GARCH and LSTM variants with a Temporal Fusion Transformer model.

4.3.1 ARIMA-GARCH Modeling

The first stage of the forecasting process utilizes a hybrid ARIMA-GARCH model:

1. ARIMA Modeling: An Autoregressive Integrated Moving Average model is fitted on train set with target and PCs from PCA as exogenous variables. The order (p,d,q) of ARIMA model is determined using auto arima, an algorithm that automatically finds optimal order parameters and with the help of Augmented Dickey–Fuller test and ACF & PACF plot to limit the range of search space.
2. GARCH Modeling: A Generalized Autoregressive Conditional Heteroskedasticity model is trained on the residuals obtained from ARIMA model. the GARCH model capture the volatility clustering present in the residuals. The order in model is found using grid search with criteria as AIC and BIC.
3. Prediction: Predictions are made on the validation and test set using the trained ARIMA

and GARCH models. The final prediction is the ARIMA prediction with GARCH as volatility bands.

4. Residual Extraction: Residuals are calculated by subtracting the final prediction from actual values.

4.3.2 LSTM Variants and Temporal Fusion Transformer Model

1. **LSTM Variants**:
    - The residuals from the validation and test sets are used as the training and testing data for the LSTM variants. The LSTM variants include traditional LSTM, BiLSTM, Attention LSTM, and Attention BiLSTM.
    - Since we want to forecast price values for next 7 days. The time-series datasets are created with a look-back period of 7 days.
    - Hyperparameter tuning is performed using BayesSearch to find the optimal hyperparameters for each LSTM variant. The BayesSearch is conducted on the training set.
    - The best model from each variant, as determined by BayesSearch, is used to predict the residuals in the test set.
2. **Temporal Fusion Transformer (TFT) Model**: The validation and test sets residuals are also used to hyperparameter tuning and test on Temporal Fusion Transformer model.
3. **Final Prediction**: The final predicted result is calculated by combining the ARIMA-GARCH prediction with the predictions from the best-performing LSTM variant or TFT model, leveraging their complementary strengths.[2]

4.4 PERFORMANCE MEASUREMENTS

Several quantitative metrics and diagnostic tests are employed across different stages of the methodology to evaluate the performance of the proposed forecasting models comprehensively.

- **Stationary Testing**:
  The Augmented Dickey-Fuller test is applied to the target close price to assess its stationarity. As a result, a p-value larger than 0.05 indicates non-stationary and needs differencing once.
- **Model Order Selection for ARIMA-GARCH**:
  For the ARIMA-GARCH framework, the best order parameters are selected based on 2 statistical tool:
    - Akaike information Criterion (AIC): Evaluates the goodness of fit and simplicity of a model. Where lower AIC values indicate better models. AIC favors simpler models over complex ones if they have similar accuracy. [7]
    - Bayesian Information Criterion (BIC): Similar to AIC but penalizes complexity more heavily. Also prefer lower values. BIC is more conservative than AIC, making it suitable for longer-term forecasting. [8]

  These criteria balance model fit with complexity, aiding in the identification of a parsimonious model that adequately captures the underlying data dynamics.
- **Evaluate LSTM variants and TFT models**:
  To compare and evaluate the performance among these models, the following error metrics are utilized:
    - Mean Squared Error (MSE): Measure the average squared difference between the estimated values and the true value.
    - Root Mean Squared Error (RMSE): Measures the square root of the average squared errors, thereby penalizing larger errors more heavily.
    - Mean Absolute Error (MAE): Provides a measure of the average magnitude of forecast errors without considering their direction.
    - Symmetric Mean Absolute Percentage Error (MAPE): Offers a measure of forecast accuracy that is particularly useful for comparing performance across different scales.
    - R-squared (R^2): A statistical measure that represents the proportion of the variance for a dependent variable that's explained by an independent variable.

5. RESULTS

The data collection spanned from November 16, 2014, to November 16, 2024. Using the Yfinance package, which is a python library to scrape data from Yahoo Finance site, we collected 3654 records of bitcoin price information. Similarly, records for commodities (Gold & Oil), stock indexes (Dow Jones, NASDAQ, S&P500,...), and other minors are collected with missing dates so we have to use imputation and linear interpolation to fill out those gaps. Additionally, the Pytrends library is utilized to take the search volume of Bitcoin-related terms from Google. Lastly, blockchain info is collected from Blockchain.com site through their API calls. The final total data set includes 3654 rows.

5.1 DATA INTERPRETATION

A detailed decomposition of the Bitcoin price series was performed to analyze underlying seasonalities and trends Fig. 2. The analysis revealed clear seasonal patterns, with recurring fluctuations that suggest periodic influences on Bitcoin's price. The overall trend shows a strong upward trajectory, particularly after 2020, with significant volatility. While market noise contributes to short-term fluctuations, the decomposition indicates both trend and seasonality as key drivers of price movement. Descriptive statistical measures showed that Bitcoin's price distribution was positively skewed, indicating a propensity for occasional extreme high values, while several exogenous variables, particularly those derived from sentiment and blockchain metrics, exhibited leptokurtic characteristics—suggesting a higher likelihood of extreme deviations.

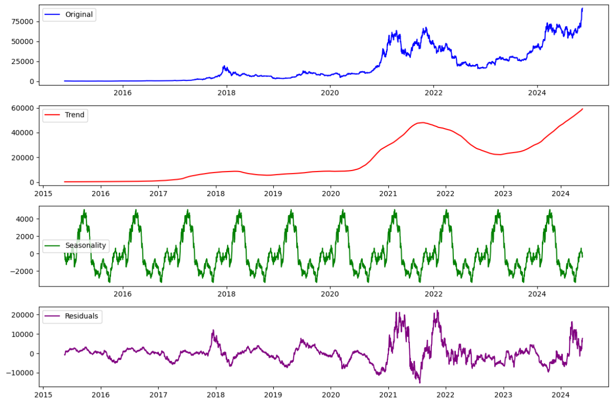

Fig. 2: Seasonal Decomposition

Prior to model implementation, the stationarity of the Bitcoin price series was rigorously tested using the Augmented Dickey-Fuller (ADF) test Fig. 3. Results confirmed that while the original series contained a unit root, a first-order differencing successfully achieved stationarity. This step was critical to ensuring the appropriateness of subsequent time-series models, particularly for the ARIMA-GARCH framework.

Metric	Before Differencing	After Differencing
ADF Statistic	0.293458	-8.360576e+00
p-value	0.977042	2.830894e-13
1% Critical Value	-3.432156	-3.432157e+00
5% Critical Value	-2.862338	-2.862338e+00
10% Critical Value	-2.567195	-2.567195e+00

Fig. 3: ADF test results

Correlation analysis Fig. 4 among the exogenous variables revealed several strong interdependencies, prompting the use of PCA to reduce dimensionality and mitigate redundancy. As shown in Fig. 5, the first principal component (PC1) explains approximately 56% of the total variance, while the second (PC2) and third (PC3) account for around 10% each. By the fourth principal component, the cumulative explained variance exceeds 85%, indicating that a few PCs capture the bulk of the data's informational content. Technical indicators and market metrics with high pairwise correlations are effectively consolidated into these significant components, thus enhancing the signal-to-noise ratio and yielding a more robust basis for subsequent modeling.

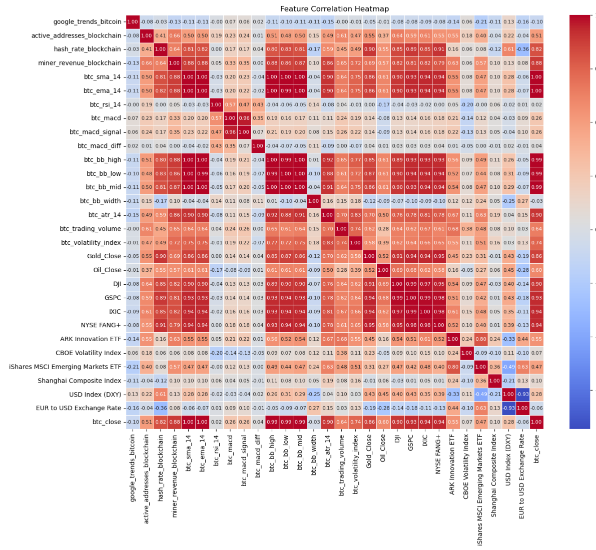

Fig. 4: Feature Correlation Heatmap

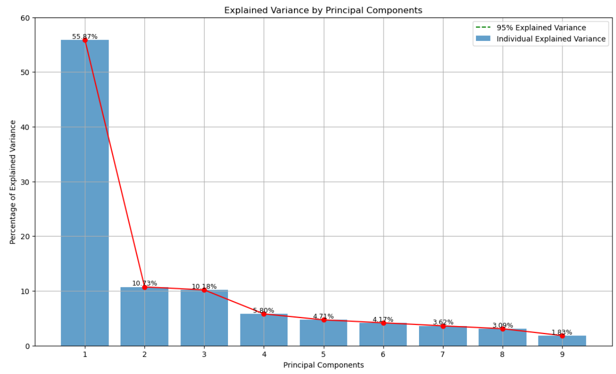

Fig. 5: Scree plot of principal components

5.2 FITTING MODELS WITH ARIMA GARCH

After preprocessing, an ARIMA(p,d,q) model was fitted to the training set using AIC and BIC for parameter selection. The auto-arima was utilized to identify the optimal parameter set.

The results of the statistical tests conducted on the residuals of the ARIMA model indicate that while the model has successfully captured the time-dependent structure of the Bitcoin closing prices, it fails to account for the changing variance over time. The Ljung-Box test Fig. 6a confirms that the residuals are white noise, suggesting that ARIMA has adequately removed autocorrelation and modeled the underlying trend and seasonality. However, the ARCH-LM test Fig. 6b detects significant heteroskedasticity, indicating the presence of volatility clustering, a common characteristic in financial time series. This finding suggests that the variance of residuals is not constant, violating the assumption of homoskedasticity in ARIMA models. Given this, applying a GARCH model in combination with ARIMA is necessary to effectively model the dynamic nature of volatility. While ARIMA captures the mean process, GARCH is required to model the time-varying conditional variance, ensuring a more robust and accurate representation of Bitcoin price movements.

```
Ljung-Box Test Results:
     lb_stat  lb_pvalue
10  0.557445   0.999989
✅ Fail to Reject Null: Residuals are white noise
```

(a) Ljung-Box Test

```
ARCH-LM Test Results:
LM Statistic: 190.4406431775069
P-value: 1.583000477766743e-35
❌ Reject Null: Residuals exhibit heteroskedasticity
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(b) ARCH LM Test

Fig. 6: Statistical tests conducted on residual

The in-sample prediction Fig. 7 suggest that the ARIMA model appears to capture most of the variance, as evidenced by an R^2 of about 0.9989. The MSE (20,109.96) and RMSE (141.84) indicate that, on average, predictions deviate from actual values by around 142 units. The MAE of 66.89 shows a typical absolute error in the tens range. However, the very high MAPE (over 1,276%) suggests that relative errors may be extremely large for certain points, possibly due to small actual values or outliers. This discrepancy highlights the importance of looking beyond a single error metric and verifying that your chosen metrics are appropriate for the data's scale and distribution.

Model	AIC	BIC	MSE	RMSE	MAE	MAPE	R2
ARIMA	-11003.836167	-10924.14658	20119.695765	141.843913	66.818863	1.276746	0.998907

Fig. 7: ARIMA In-Sample Prediction

Subsequently, the residuals from the ARIMA model were employed to fit a GARCH(r,s) model, using grid search to find the best way to capture volatility clustering in the data.

The ARIMA model's actual prediction was compared against actual Bitcoin prices on the validation and test sets to evaluate the performance Fig. 8. The MSE, RMSE, MAE, MAPE values appear really bad, the negative R^2 also indicate that ARIMA model alone really struggles to capture the complexities of Bitcoin's price movements. This underperformance is likely due to high volatility and non-linear dynamics inherent in cryptocurrency markets since ARIMA model can only handle linear trends in time series data.

Metric	sarima_val	sarima_test
MSE	6.909327e+08	1.012415e+09
RMSE	2.628560e+04	3.181847e+04
MAE	2.131962e+04	2.579572e+04
MAPE	4.881029e-01	5.240261e-01
R2	-2.759713e+00	-1.901124e+00

Fig. 8: ARIMA Prediction Error on Val & Test

5.3 FITTING MODELS WITH LSTM & TFT

To capture the nonlinear patterns in residuals, we will feed residuals obtained from the ARIMA-GARCH model as input features and the Bitcoin daily closing price as the final prediction target, we constructed multiple deep learning architectures: traditional LSTM, BiLSTM, Attention-LSTM, Attention-BiLSTM, Ensemble-LSTM, and the Temporal Fusion Transformer (TFT). The look-back window for each LSTM variant was set to 7, based on preliminary autocorrelation analysis of the residuals. The hidden layers in each model employed the ReLU activation function, with a linear activation in the final dense output layer. Hyperparameter optimization was carried out using a Bayesian search strategy, as recommended by [9], to determine optimal settings for number of attention head, dropout rate, learning rate, batch size, and number of neurons in each layer.

The performance metrics—MSE, RMSE, MAE, MAPE, and R^2 —for the LSTM variants and TFT model are presented in Fig. 9. All deep learning models demonstrated improved predictive capabilities compared to the standalone ARIMA-GARCH model, underscoring the effectiveness of capturing nonlinear features in Bitcoin's price movements. Among the LSTM variants, the Ensemble-LSTM model yielded the lowest error rates (MSE: 3.5e7; RMSE: 6e3; MAE: 4e3; MAPE: 0.089) and the highest R^2 (0.89). However, the Temporal Fusion Transformer emerged as the best-performing model overall, with the lowest MSE (1.6e7), RMSE (4e3), MAE (2.4e3), and MAPE (0.0474), as well as the highest R^2 (0.95). These results highlight the advantage of attention-based architectures like TFT in handling complex dependencies and volatility patterns. Proving that the TFT model maintains a closer track of price fluctuations even during sudden market shifts. This superior performance can be attributed to its multi-headed attention mechanism and its ability to incorporate both static and time-varying covariates more effectively. Overall, the incorporation of deep learning—particularly attention-based models—proves crucial for capturing the nonlinear and high-volatility nature of cryptocurrency time series, thereby enhancing forecast accuracy beyond traditional econometric methods.

	LSTM	BiLSTM	Attention-LSTM	Attention-BiLSTM	Ensemble-LSTM	Temporal-Fusion-Transformer
MSE	59,442,043.3125	36,266,602.1158	58,194,353.3725	57,300,490.5465	34,592,440.7264	16,220,333.4204
RMSE	7,709.8666	6,022.1759	7,628.5224	7,569.7087	5,881.5339	4,027.4475
MAE	5,085.7016	4,059.3677	5,003.4728	4,884.5025	3,860.8966	2,432.1452
MAPE	0.1028	0.0944	0.1008	0.1055	0.0833	0.0474
R2	0.8281	0.8951	0.8317	0.8343	0.8999	0.9531

Fig. 9: LSTM Variants and TFT evaluation metrics

5.4 Forecasting with LSTM & TFT

In this final stage, the forecasted result is calculated by combining the ARIMA-GARCH prediction with the predictions from the best-performing LSTM variant or TFT model. Fig. 10 illustrates the forecasts of the ARIMA Temporal Fusion Transformer Hybrid model, which is the best performance model based on evaluation metrics above.

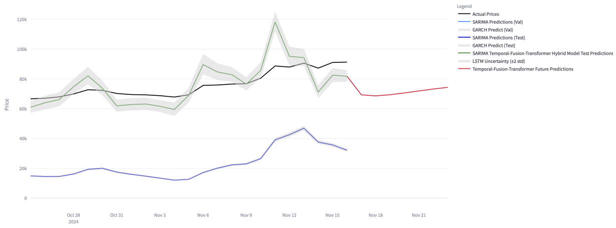

Fig. 10: ARIMA Temporal Fusion Transformer Hybrid Model Forecast

6. CONCLUSION

In this study, we proposed a hybrid framework for short-term Bitcoin price forecasting, integrating statistical and deep learning approaches. Our methodology began with data preprocessing Principal Component Analysis (PCA) to reduce dimensionality, and address multicollinearity among exogenous variables. We then employed an ARIMA-GARCH model to capture linear dependencies and volatility clustering. Residuals from this model served as inputs to multiple deep learning architectures—traditional LSTM, BiLSTM, Attention-LSTM, Attention-BiLSTM, Ensemble-LSTM, and the Temporal Fusion Transformer (TFT)—to account for nonlinear relationships and complex temporal patterns.

Experimental results showed that while ARIMA-GARCH provides a solid baseline, it struggles to accommodate the high volatility and nonlinearities inherent in Bitcoin price movements. By contrast, the LSTM variants significantly improved forecasting accuracy, highlighting their capacity to extract features from residual signals. Notably, the Temporal Fusion Transformer outperformed all other models, demonstrating superior performance metrics across the validation and test sets. These findings underscore the efficacy of attention-based architectures in handling intricate temporal dependencies and capturing sudden market fluctuations.

Overall, the proposed hybrid pipeline—combining traditional econometric techniques with advanced deep learning models—offers a robust and scalable solution for forecasting highly volatile financial time series. Future work could explore additional sentiment data sources, employ more sophisticated volatility models, and investigate interpretability methods to further elucidate the factors driving Bitcoin price dynamics.

7. FUTURE WORK

There are several directions in which this research can be extended. First, an enhanced Empirical Mode Decomposition (EMD) approach could be applied directly to the target variable—Bitcoin's closing price—to decompose it into Intrinsic Mode Functions (IMFs). By forecasting each IMF independently, one could potentially isolate distinct frequency components, thereby improving the overall prediction accuracy once these signals are recombined. Second, more advanced Transformer-based architectures could be explored, building on the promising results demonstrated by the Temporal Fusion Transformer (TFT). For example, experimenting with larger or more specialized attention mechanisms, or incorporating external attention modules, may further capture the complex temporal dependencies inherent in Bitcoin price data. Ultimately, these avenues offer promising opportunities to refine both the interpretability and predictive power of hybrid forecasting models in the cryptocurrency domain.

REFERENCES

[1] Bryan Lim, Sercan O. Arik, Nicolas Loeff, and Tomas Pfister. Temporal fusion transformers for interpretable multi-horizon time series forecasting. *arXiv preprint arXiv:1912.09363*, Dec. 2019. doi: arXiv.1912.09363.

[2] A. Mardjo and C. Choksuchat. Hybilstm: Multivariate bitcoin price forecasting using hybrid time-series models with bidirectional lstm. In *Proc. IEEE Access*, volume 12, pages 50792–50808, Dec. 2024. doi: 10.1109/ACCESS.2024.3386029.

[3] Sahar Erfanian, Yewang Zhou, Amar Razzaq, Azhar Abbas, Asif Ali Safeer, and Teng Li. Predicting bitcoin (btc) price in the context of economic theories: A machine learning approach. *Entropy*, 24(10):1487, Oct. 2022. doi: 10.3390/e24101487.

[4] Abdelatif Hafid, Mohamed Rahouti, Linglong Kong, Maad Ebrahim, and Mohamed Adel Serhani. Predicting bitcoin market trends with enhanced technical indicator integration and classification models. *arXiv*, 2410.06935, Oct. 2024. doi: 10.48550/arXiv.2410.06935.

[5] Hae Sun Jung, Seon Hong Lee, Haein Lee, and Jang Hyun Kim. Predicting bitcoin trends through machine learning using sentiment analysis with technical indicators. *Computer Systems Science and Engineering*, 46:2231–2246, 2023. doi: 10.32604/csse.2023.034466.

[6] Mohammed Mudassir, Shada Bennbaia, Devrim Unal, and Mohammad Hammoudeh. Time-series forecasting of bitcoin prices using high-dimensional features: a machine learning approach. *Neural Computing and Applications*, 2020. doi: 10.1007/s00521-020-05129-6.

[7] H. Akaike. A new look at the statistical model identification. *IEEE*, 19(6):716–723, Dec. 1974. doi: 10.1109/TAC.1974.1100705.

[8] Gideon Schwarz. Estimating the dimension of a model. *IEEE*, 19(6):461 – 464, Mar. 1978. doi: 10.1214/aos/1176344136.

[9] Eric Brochu, Vlad M. Cora, and Nando De Freitas. A tutorial on bayesian optimization. *arXiv preprint arXiv:1807.02811*, 2010. doi: 10.48550/arXiv.1807.02811.

[10] K. Srijiranon, Y. Lertratanakham, and T. Tanantong. A hybrid framework using pca, emd and lstm methods for stock market price prediction with sentiment analysis. *Applied Sciences*, 12(21):10823, 2022. doi: 10.3390/app122110823.

[11] A. A. Abdelhamid, E. M. El-Kenawy, B. Alotaibi, G. M. Amer, M. Y. Abdelkader, A. Ibrahim, and M. M. Eid. Robust speech emotion recognition using cnn+lstm based on stochastic fractal search optimization algorithm. In *Proc. IEEE Access*, volume 10, pages 49265–49284, Dec. 2022. doi: 10.1109/ACCESS.2022.3172954.

[12] W. Chen, H. Xu, L. Jia, and Y. Gao. Machine learning model for bitcoin exchange rate prediction using economic and technology determinants. In *Proc. Int. J. Forecasting*, volume 37, pages 28–43, Jan. 2021. doi: 10.1016/j.ijforecast.2020.02.008.

[13] A. Dutta, S. Kumar, and M. Basu. A gated recurrent unit approach to bitcoin price prediction. In *Proc. J. Risk Financial Manage.*, volume 13, page 23, Feb. 2020. doi: 10.3390/jrfm13020023.

[14] S. Hansun, A. Wicaksana, and A. Q. M. Khaliq. Multivariate cryptocurrency prediction: Comparative analysis of three recurrent neural networks approaches. In *Proc. J. Big Data*, volume 9, page 50, Apr. 2022. doi: 10.1186/s40537-022-00601-7.

[15] F. Valencia, A. Gómez-Espinosa, and B. Valdés-Aguirre. Price movement prediction of cryptocurrencies using sentiment analysis and machine learning. In *Proc. Entropy*, volume 21, page 589, Jun. 2019. doi: 10.3390/e21060589.

[16] H. Jang and J. Lee. An empirical study on modeling and prediction of bitcoin prices with bayesian neural networks based on blockchain information. In *Proc. IEEE Access*, volume 6, pages 5427–5437, 2018. doi: 10.1109/ACCESS.2017.2779181.

[17] X. Li and C. A. Wang. The technology and economic determinants of cryptocurrency exchange rates: The case of bitcoin. In *Proc. Decis. Support Syst.*, volume 95, pages 49–60, Mar. 2017. doi: 10.1016/j.dss.2016.12.001.

[18] O. Poyser. Exploring the determinants of bitcoin's price: An application of bayesian structural time series. In *Proc. arXiv*, 2017. arXiv: 1706.01437.

[19] S. Palamalai, B. Maity, and K. Kumar. Macrofinancial parameters influencing bitcoin prices: Evidence from symmetric and asymmetric ardl models. In *Proc. Rev. Econ. Anal.*, volume 13, pages 143–175, Oct. 2021. doi: 10.15353/rea.v13i3.3585.

[20] T. Panagiotidis, T. Stengos, and O. Vravosinos. On the determinants of bitcoin returns: A lasso approach. In *Proc. Finance Res. Lett.*, volume 27, pages 235–240, Dec. 2018. doi: 10.1016/j.frl.2018.03.016.

[21] T. Panagiotidis, T. Stengos, and O. Vravosinos. The effects of markets, uncertainty and search intensity on bitcoin returns. In *Proc. Int. Rev. Financial Anal.*, volume 63, pages 220–242, May. 2019. doi: 10.1016/j.irfa.2018.11.002.

[22] S. Dastgir, E. Demir, G. Downing, G. Gozgor, and C. K. M. Lau. The causal relationship between bitcoin attention and bitcoin returns: Evidence from the copula-based granger causality test. In *Proc. Finance Res. Lett.*, volume 28, pages 160–164, Mar. 2019. doi: 10.1016/j.frl.2018.04.019.

[23] J. Abraham, D. W. Higdon, J. Nelson, and J. Ibarra. Cryptocurrency price prediction using tweet volumes and sentiment analysis. In *Proc. SMU Data Sci. Rev.*, volume 1, pages 1–22, 2018.

[24] Y. B. Kim, J. G. Kim, W. Kim, J. H. Im, T. H. Kim, S. J. Kang, and C. H. Kim. Predicting fluctuations in cryptocurrency transactions based on user comments and replies. In *Proc. PLoS ONE*, volume 11, Aug. 2016. Art. no. e0161197.

[25] E. Bouri, P. Molnár, G. Azzi, D. Roubaud, and L. I. Hagfors. On the hedge and safe haven properties of bitcoin: Is it really more than a diversifier? In *Proc. Finance Res. Lett.*, volume 20, pages 192–198, Feb. 2017.

[26] Y. Zhu, D. Dickinson, and J. Li. Analysis on the influence factors of bitcoin's price based on vec model. In *Proc. Financial Innov.*, volume 3, pages 1–13, Dec. 2017. doi: 10.1186/s40854-017-0054-0.

[27] S. Pyo and J. Lee. Do fomc and macroeconomic announcements affect bitcoin prices? In *Proc. Finance Res. Lett.*, volume 37, Nov. 2020. Art. no. 101386, doi: 10.1016/j.frl.2019.101386.

[28] J. Wang, F. Ma, E. Bouri, and Y. Guo. Which factors drive bitcoin volatility: Macroeconomic, technical, or both? In *Proc. J. Forecasting*, volume 42, pages 970–988, Nov. 2022. doi: 10.1002/for.2930.

[29] G. P. Zhang. Time series forecasting using a hybrid arima and neural network model. In *Proc. Neurocomputing*, volume 50, pages 159–175, Jan. 2003. doi: 10.1016/s0925-2312(01)00702-0.

[30] R. J. Brenner, R. H. Harjes, and K. F. Kroner. Another look at models of the short-term interest rate. In *Proc. J. Financial Quant. Anal.*, volume 31, pages 85–107, Mar. 1996.

[31] M. Yeasin, K. Singh, A. Lama, and R. Paul. Modelling volatility influenced by exogenous factors using an improved garch-x model. In *Proc. J. Indian Soc. Agricult. Statistic*, volume 74, pages 209–216, Dec. 2020.

[32] M. M. Patel, S. Tanwar, R. Gupta, and N. Kumar. A deep learning-based cryptocurrency price prediction scheme for financial institutions. In *Proc. J. Inf. Secur. Appl.*, volume 55, Dec. 2020. Art. no. 102583, doi: 10.1016/j.jisa.2020.102583.

[33] L. Yu, S. Liang, R. Chen, and K. K. Lai. Predicting monthly biofuel production using a hybrid ensemble forecasting methodology. In *Proc. Int. J. Forecasting*, volume 38, pages 3–20, Jan. 2022. doi: 10.1016/j.ijforecast.2019.08.014.

[34] A. N.-L. Huynh, R. C. Deo, D.-A. An-Vo, M. Ali, N. Raj, and S. Abdulla. Near real-time global solar radiation forecasting at multiple time-step horizons using the long short-term memory network. In *Proc. Energies*, volume 13, page 3517, Jul. 2020. doi: 10.3390/en13143517.

[35] M. Schuster and K. K. Paliwal. Bidirectional recurrent neural networks. In *Proc. IEEE Trans. Signal Process.*, volume 45, pages 2673–2681, Nov. 1997. doi: 10.1109/78.650093.

[36] D. Bahdanau, K. Cho, and Y. Bengio. Neural machine translation by jointly learning to align and translate. In *Proc. arXiv*, 2014. arXiv: 1409.0473.

[37] E. Nzayisenga and Y. Zhu. The import trade forecasting model based on pca: Evidence from rwanda. In *Proc. Open J. Statist.*, volume 10, pages 678–693, Jan. 2020. doi: 10.4236/ojs.2020.104042.

[38] Hult G. T. M. Ringle C. M. Sarstedt M. Hair, J. F. *A Primer on Partial Least Squares Structural Equation Modeling (PLS-SEM)*. Sage, Thousand Oaks, CA, USA, 2nd edition, 2017. doi: http://study.sagepub.com/hairprimer2e.

[39] T. I. Okedi and A. C. Fisher. Time series analysis and long short-term memory (lstm) network prediction of bpv current density. In *Proc. Energy Environ. Sci.*, volume 14, pages 2408–2418, Apr. 2021. doi: 10.1039/d0ee02970j.

[40] M. Roondiwala, H. Patel, and S. Varma. Predicting stock prices using lstm. In *Proc. Int. J. Sci. Res.*, volume 6, pages 1754–1756, Apr. 2017. doi: 10.21275/ART20172755.

[41] M. M. Eid, E.-S.-M. El-Kenawy, N. Khodadadi, S. Mirjalili, E. Khodadadi, M. Abotaleb, A. H. Alharbi, A. A. Abdelhamid, A. Ibrahim, G. M. Amer, A. Kadi, and D. S. Khafaga. Meta-heuristic optimization of lstm-based deep network for boosting the prediction of monkeypox cases. In *Proc. Mathematics*, volume 10, page 3845, Oct. 2022. doi: 10.3390/math10203845.

[42] Xingdan Huang, Panlu You, Xiaolian Gao, and Dapeng Cheng. Stock price prediction based on arima-garch and lstm. In *Proc. Int. Conf. on Business Intelligence and Security (ICBIS)*, volume 14, pages 438–448, 2023. doi:10.2991/978-94-6463-198-$2_4 5$.