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Deep Learning and Machine Learning Insights Into the Global Economic Drivers of the Bitcoin Price

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ABSTRACT

This study examines the connection between Bitcoin and global factors, including the VIX, the oil price, the US dollar index, the gold price, and interest rates estimated using the Federal funds rate and treasury securities rate, for forecasting analysis. Deep learning methodologies, including LSTM, GRU, CNN, and TFT, with machine learning algorithms such as XGBoost, LightGBM, and SVR, were employed to identify the optimal prediction model for the Bitcoin price. The findings indicate that the TFT model is the most successful predictive approach, with the gold price identified as the most relevant component in determining the Bitcoin price. After the gold indicator, the US dollar index was a substantial factor in the explanation of the Bitcoin price. The TFT model also included regulatory decisions and global events. It was estimated that the Bitcoin price was significantly influenced by the COVID-19 pandemic. After that, global climate events and China mining ban strongly affected the Bitcoin price. These findings indicate that regulatory decisions and global events determine the Bitcoin price in addition to macroeconomic factors. The VAR analysis was employed as a robustness check. The results indicate that gold and oil prices have a strong negative influence on Bitcoin, particularly in the long term. The paper has significant policy implications for investors, portfolio managers, and scholars.

JEL Classification: B17, C32, C50

1 | Introduction

This study aims to provide a framework that analyses the effects of macroeconomic and event-based factors and comparatively evaluates traditional econometric methods with machine and deep learning (DL) models to improve the predictability of the Bitcoin price. In this context, the impact of macroeconomic variables and regulatory events are analyzed using advanced machine learning (ML) and econometric models. The aim of the study is to provide a better understanding of the factors affecting the Bitcoin price and to offer a guide to use this knowledge to improve forward forecasting performance. In recent years, Bitcoin has become the most well-known and most traded asset of cryptocurrencies in financial markets. Introduced in 2008 as the first decentralized cryptocurrency that allows non-intermediated peer-to-peer transactions, Bitcoin attracted investors' attention with its innovative structure and led to an increase in market activity (Sabry et al. 2020; Aljaed 2024). Its strong brand identity, loyal user base, and the potential of blockchain technology to transform financial systems have increased Bitcoin's appeal (Kufo, Gjeci, and Pilkati 2023). By the end of 2021, Bitcoin's market capitalization reached approximately $930 billion, making it the largest cryptocurrency (Majeed, Ali, and Mohammed 2023). The high market capitalization and trading volume had a positive correlation with prices, creating

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a feedback loop in which increased demand and investment activity pushed prices even higher (Juwita, Ramadhani, and Maris 2023). Moreover, investments in Bitcoin by large companies such as Tesla and MicroStrategy supported its transformation from a speculative asset to a legitimate investment vehicle, reaching more investors through futures and ETFs (Sabry et al. 2020; Sebastião and Godinho 2020). The main aim of this work is to examine the movements of the Bitcoin price by using DL and ML methodologies. Hence, there are important questions to ask. Which variables are the most important in Bitcoin price forecasting? Which global factors affect the forecasting performance more? To what extent are DL and ML models successful in Bitcoin price prediction? Which model shows the highest performance? What are the performance differences between different models (Convolutional Neural Network [CNN], Gated Recurrent Unit [GRU], Long Short-Term Memory [LSTM], LightGBM, XGBoost, Support Vector Regression [SVR], and Temporal Fusion Transformer [TFT]) in predicting the Bitcoin price? How do global factors affect the Bitcoin price in the short and medium term? This study aims to provide solutions to these issues. This paper employs unique methodologies, marking the first instance of Bitcoin price analysis via the lens of global factors using DL and ML techniques. This research is expected to have substantial policy implications for investors, portfolio managers, and scholars.

Bitcoin's volatility is an important factor that attracts investors' interest. The volatility of the cryptocurrency market is characterized by extreme price changes in a short period of time, especially in Bitcoin (Haj and Moustafa 2023). This volatility is influenced by factors such as market sentiment, regulatory developments, and macroeconomic trends (Sakas et al. 2023). As a high-risk investment instrument, Bitcoin encourages speculative trading and increases market participation (Haj and Moustafa 2023). Being seen as a "safe haven" in times of economic uncertainty has led Bitcoin to be perceived as an alternative investment instrument to gold (Guo 2023). Its decentralized structure, which offers speed and low cost in cross-border transactions, makes Bitcoin attractive for developing countries (Sabry et al. 2020). Regulatory developments also shape Bitcoin's market dynamics, with clear regulations boosting trust while excessive restrictions may hinder innovation (Sakas et al. 2023). Thus, Bitcoin's high market capitalization and institutional acceptance suggest that it will continue to play an important role in the long run. Bitcoin's high market cap and growing institutional acceptance continues to be discussed in the literature for its complex behavior during economic and geopolitical crises. For instance, during the COVID-19 pandemic, prices initially fell as investors turned to liquidity (Omane-Adjepong, Alagidede, and Dramani 2021; Jana and Sahu 2023), but subsequently rose, which can be considered a hedge against inflation and economic instability (Grira, Guizani, and Kahloul 2022). However, while some studies suggest that Bitcoin can be a safe haven against economic downturns (Su et al. 2022), others emphasize that its speculative nature and sensitivity to market sentiment limit its stability (Mnif, Mouakhar, and Jarboui 2022). Moreover, Bitcoin's market dynamics are also affected by geopolitical tensions such as the Russia–Ukraine war; in this context, geopolitical risk has been stated to have a significant impact on prices (Bangun and Warganegara 2023).

Forecasting the Bitcoin price has become increasingly important due to the cryptocurrency's volatility and impact on global financial markets. Unpredictable price movements increase the need for advanced analytical methods in risk management for both individual and institutional investors (Cretarola and Figà-Talamanca 2019; Zhang et al. 2021). The Bitcoin price is influenced by factors such as market sentiment, trading volume, and macroeconomic indicators, requiring investors to resort to sophisticated models to maximize gains and minimize losses (Zulfiqar and Gulzar 2021; Perić, Smiljanić, and Jerković 2023). Institutional investors use Bitcoin price forecasts for portfolio diversification and risk management strategies (Caporale and Kang 2020), while retail investors use them to identify entry and exit points for speculative trading (Blasco, Corredor, and Satrústegui 2022). Moreover, social media and online platforms guide individual investors' decisions through sentiment analysis and technical indicators (Hudson and Urquhart 2019). Regulators use price forecasts to understand risks in the financial system and ensure market stability (Guo et al. 2021). The interaction of the Bitcoin price with macroeconomic factors such as geopolitical risks and economic uncertainties causes forecasting models to become more complex, and more robust models need to be developed (Zhang 2022; Cheng et al., 2024). In this context, accurate forecasting methods play a central role in strategy and policy development for investors and regulators.

The growing popularity of artificial intelligence (AI) techniques such as ML and DL in financial forecasting is due to their capacity to process big data and their ability to understand complex relationships relative to traditional statistical methods. Financial markets generate a variety of data such as trading volume, price movements, and social media sentiment; accurate analysis of this data is critical for forecast accuracy (Mogaji, Soetan, and Kieu 2020; Hassani and Silva 2024). While traditional methods fail to understand these non-linear relationships, AI techniques can successfully capture these complexities (Makridakis, Spiliotis, and Assimakopoulos 2018). AI also improves with new data, quickly adapting to changing market conditions and increasing forecasting accuracy (Tandiono 2023). Algorithms such as LSTM also outperform traditional methods by providing more accurate forecasts on time series data (Hassani and Silva 2024). The accessibility of AI tools has led to wider adoption of these techniques, increasing their use among individual investors (Tandiono 2023). The popularity of AI in financial forecasting is based on its accuracy, speed, and adaptability.

The use of ML and DL techniques in Bitcoin price forecasting is increasingly favored due to the complex nature and high volatility of the cryptocurrency market. While traditional statistical methods cannot adequately capture Bitcoin's irregular price movements, ML and DL models can effectively model the non-linear relationships between variables such as market sentiment, macroeconomic indicators, and social media trends (Siva, Subrahmanian, and Chaturya 2024). In particular, DL architectures such as LSTM and GRU are well suited for Bitcoin price prediction due to their capacity to learn long-term dependencies

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in time series data (Jin and Li 2023; Ula, Ilhadi, and Sidek 2024). These techniques have been shown to process large data sets quickly, allowing traders to react quickly and strategically to market fluctuations (Liu et al. 2021; Tripathy, Hota, and Mishra 2023). Moreover, the continuous learning capabilities of ML and DL algorithms increase the prediction accuracy over time, giving investors an advantage in making informed decisions (Jin and Li 2023; Nair, Marie, and Abd-Elmegid 2023). The integration of these techniques into Bitcoin price forecasting will play an increasingly important role in financial analysis processes by providing investors with a strategic advantage.

The aim of this study is to measure the predictability of the Bitcoin price using various ML and DL models and evaluate their performance. The models used include CNN, GRU, LSTM, LightGBM, XGBoost, SVR, and TFT. In addition, the hyperparameter settings of these models were adjusted using advanced hyperparameter optimization methods such as Optuna and RandomSearchCV. In this study, several global variables such as VIX (Volatility Index), Oil price, DXY (US Dollar Index), Gold price, DGS5 (5-Year US Bond Yield), and DFF (Federal Funds Rate) are included in the modeling. The dataset covers daily data from January 2012 to February 2024. Significant global events during this period led to complex patterns in Bitcoin price dynamics and made price forecasts difficult. In particular, the COVID-19 pandemic (March 2020 to December 2021) caused fluctuations in Bitcoin price due to the global economic recession and increased uncertainty in the markets. In addition, Central Bank Monetary Policies, especially the expansionary policies and interest rate changes implemented by the US Federal Reserve (Fed), affected the attractiveness of crypto assets for investors. Other major events during this period included oil-related tensions in the Middle East (especially the massive drop in the oil price in 2014–2016) and the Russian-Ukrainian War (which started in February 2022), which indirectly affected global energy markets and thus the Bitcoin price. Regulatory developments in the cryptocurrency market also had a decisive impact on the Bitcoin price; for example, China's ban on Bitcoin mining and restrictions on cryptocurrency exchanges (especially the ban imposed in May 2021) led to significant fluctuations in the Bitcoin market. Moreover, increasing inflationary pressures and global economic uncertainties during the period led to the adoption of Bitcoin as a store of value. In addition, the Bitcoin bull run in 2017 and speculative movements in the market led to spikes in the Bitcoin price. These events and unusual circumstances have created complex patterns that complicate Bitcoin price forecasts, making it difficult to predict price dynamics. For these reasons, this study aims to identify the most successful forecasting model by comparing different modeling techniques and analyzing the decision-making processes behind these models. In particular, we will examine which variables are more important for the model with the best forecasting performance and discuss the role of these variables in Bitcoin price forecasting in more detail. In addition, the VAR analysis will also examine and analyze the impact of shocks to global variables in certain ratios on the Bitcoin price in the short and medium term. The results of the study have important implications for investors and policymakers who want to predict the future directions of financial markets and cryptocurrencies.

2 | Previous Research and the Current Work

2.1 | Previous Research

The existing literature examines the success of different modeling approaches used in Bitcoin price forecasting and the effects of macroeconomic factors on the Bitcoin price. The effects of variables such as VIX, the oil price, DXY, the gold price, DGS5, and DFF on the Bitcoin price have been widely studied. The VIX has a strong relationship with the Bitcoin price as a measure of market risk and investor sentiment; in particular, Bitcoin volatility has been observed to increase during periods of heightened market uncertainty (Korauš et al. 2021; Lee and Rhee 2022). Market sentiment refers to the effect of investors' perceptions and emotional reactions on price movements, and various studies in the literature have shown that this effect is important. In particular, VIX is widely used as a proxy variable for market sentiment. The VIX's ability to capture factors such as investor fear or uncertainty is seen as a valuable tool to explain the volatility in the Bitcoin price. In the current study, the use of the VIX to understand its effects on market sentiment and to model the Bitcoin price is consistent with this approach in the literature. Thomson Reuters MarketPsych Indices (TRMI) may be used as a sentiment measure (Aysan et al. 2023). TRMI is a Bitcoin-specific sentiment measure and includes both news-based and social media-based sentiment. TRMI is different from general sentiment measures such as VIX, EPU (Economic Policy Uncertainty Index) or Google Trends used in previous literature. While most of these measures represent broad market sentiment, TRMI provides Bitcoin-specific sentiment data, allowing for better analysis of market-specific dynamics. The choice of TRMI is based on the characteristics of the Bitcoin market and the assumption that sentiment in this market can directly influence price movements. However, a more detailed examination of the effects of other general measures of market sentiment, such as the VIX, may be useful in understanding Bitcoin's relationship to the broader financial system. The impact of the oil price on Bitcoin returns is mixed; some studies find a positive correlation, while others suggest an inverse relationship (Nasution, Sadalia, and Irawati 2023). The DXY represents the strength of the dollar, and a strong dollar generally leads to reduced demand for Bitcoin, thus having an inverse effect on the Bitcoin price (Lee and Rhee 2022; Rivai 2023). The relationship between gold and Bitcoin is complex, with some studies viewing Bitcoin as a digital alternative to gold, while others see the relationship as weak (Dyhrberg 2016; Siauwijaya and Sanjung 2022). DGS5 reflects expectations of future interest rates, and low yields may drive investors to riskier assets such as Bitcoin (Lee and Rhee 2022). DFF, on the other hand, suggests that low rates may increase demand for Bitcoin, while rising rates may decrease it (Aboura 2022; Wang et al. 2022). In sum, the interaction between the Bitcoin price and macroeconomic variables such as the VIX, the oil price, DXY, the gold price, DGS5, and DFF is complex and multifaceted. While some studies point to significant relationships, others suggest that these correlations may vary depending on market conditions and investor sentiment. Understanding these dynamics is crucial for investors looking to navigate the volatile cryptocurrency market and make informed investment decisions.

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Traditional statistical methods have been widely used in Bitcoin price forecasting. ARIMA and SARIMA models are popular for time series forecasting. Studies by Huang et al. (2022) and Munim, Shakil, and Alon (2019) showed that ARIMA provides a reliable basis for Bitcoin price forecasting. Linear regression examined the impact of social media sentiment and trading volume on the Bitcoin price, but this method may not fully capture the complexity of price dynamics (Ciaian, Rajčániová, and Kancs 2015). GARCH models have been used to analyze the volatility of Bitcoin, and geopolitical risks have been shown to affect price dynamics (Aysan et al. 2019). Sentiment analysis examined the relationship between Twitter sentiment and Bitcoin price changes with traditional methods and suggested that public sentiment can be an important indicator (Critien, Gatt, and Ellul 2022). Studies examining the predictive power of trading volume have shown that volume-based strategies can increase profitability, but this relationship may vary depending on market conditions (Balcılar et al. 2017). Moreover, Bayesian regression was found to be effective in capturing Bitcoin's high volatility, and Bayesian methods outperformed linear models (Jang and Lee 2018). The VECM model was used to analyze the long-run relationships between Bitcoin and macroeconomic variables (Lee and Rhee 2022). Finally, there is evidence that ML techniques generally provide better forecasting performance compared to traditional methods (Zhu 2023).

Numerous studies have explored the use of ML and DL models to predict the Bitcoin price using various algorithms and methodologies to improve prediction accuracy. Dutta, Kumar, and Basu (2020) used a GRU model for Bitcoin price prediction and highlighted its effectiveness in capturing temporal dependencies in time series data. The study reported that the GRU model outperforms traditional methods and provides high accuracy in forecasting, achieving a mean absolute percentage error (MAPE) of about 2.5%. Ula, Ilhadi, and Sidek (2024) compared the accuracy of LSTM networks and Random Forest models for Bitcoin price prediction. The results showed that the LSTM model achieved a root mean square error (RMSE) of 0.0054, while the Random Forest model had an RMSE of 0.0071, demonstrating the superior performance of LSTM in capturing the complexity of Bitcoin price movements. Ngai et al. (2023) used various ML approaches, including LSTM and Random Forest, to predict the Bitcoin price based on historical data. The study found that the LSTM model yielded an R-squared value of 0.87, indicating a strong correlation between predicted and actual prices, while Random Forest achieved an R-squared value of 0.75. Mahfooz and Phillips (2024) compare LSTM with traditional forecasting models and find that LSTM outperforms Facebook Prophet in terms of forecast accuracy, achieving a MAPE of 2.1%. In a study by Aljadani (2022), both LSTM and GRU models were applied to predict the prices of multiple cryptocurrencies, including Bitcoin. The results revealed that the LSTM model consistently outperformed the GRU. Yang (2023) used LSTM models to predict the Bitcoin price based on historical transaction data. The study reported a MAPE of 3.5% for short-term forecasts, suggesting that LSTM effectively captures the short-term dynamics of the Bitcoin price. Ye et al. (2022) developed a stacking community DL model that incorporates Twitter sentiment analysis as well as historical price data. The model achieved a prediction accuracy of 92%, highlighting the effectiveness of combining sentiment analysis with ML techniques to improve Bitcoin price predictions. Al-Zakhali and Abdulazeez (2024) conducted a comparative analysis of LSTM and GRU models for Bitcoin price prediction. The results showed that the LSTM model achieved an R-squared value of 0.92, while the GRU model had an R-squared value of 0.88, highlighting the superior performance of the LSTM in capturing complex temporal patterns. Wen and Ling (2023) compared CNNs with LSTM models for Bitcoin price prediction. The study reported that the CNN model achieved an RMSE of 0.0041, while the LSTM model had an RMSE of 0.0053, indicating that CNNs outperformed LSTMs in this particular context. Lamothe-Fernández et al. (2020) applied recurrent neural networks (RNNs) as well as CNNs to predict the Bitcoin price. The CNN model achieved an R-squared value of 0.85, indicating a strong correlation between predicted and actual prices, demonstrating the model's ability to effectively handle time series data. In the research conducted by Kar (2023), CNNs were used to predict the prices of multiple cryptocurrencies, including Bitcoin. The study revealed that the CNN model achieved an accuracy of 91%, highlighting its robustness in processing various cryptocurrency datasets. Yudono et al. (2022) applied CNNs to predict the Bitcoin price using real-time data from exchanges. The study reported a prediction accuracy of 92%, demonstrating the model's ability to adapt to rapidly changing market conditions. In a study by Liao (2023), several ML models, including MLP and SVM, were tested for Bitcoin price prediction. The MLP model outperformed SVM by achieving a mean absolute error (MAE) of 0.0035 compared to 0.0042 for SVM, demonstrating the effectiveness of MLP in capturing non-linear relationships in data. Gyamerah (2019) compared Bayesian Neural Networks (BNNs) with linear regression and SVR models for Bitcoin price prediction. The BNN model outperformed by achieving a mean squared error (MSE) of 0.0009, while the MSEs of the other models were 0.0015 and 0.0012, respectively. Alizadegan, Radmehr, and Ilani (2024) investigated the application of hybrid models combining ML and DL techniques for Bitcoin price prediction. The study reported that the hybrid model achieved an RMSE of 0.0045, outperformed individual models, and demonstrated the benefits of integrating multiple approaches. (2024) emphasized the importance of feature engineering in ML models for Bitcoin price prediction. By incorporating technical indicators such as moving averages and relative strength index (RSI), the study reported an improvement in prediction accuracy, with the model achieving an R-squared value of 0.82. Zuo (2024) conducted a comparative analysis of different ML algorithms, including LSTM, Random Forest, and XGBoost, for Bitcoin price prediction. The results showed that LSTM achieved the highest accuracy with an RMSE of 0.0042, followed by XGBoost with an RMSE of 0.0050. In a study by Guan (2022), various DL frameworks, including LSTM and CNNs, were used to predict the Bitcoin price. The LSTM model achieved a prediction accuracy of 90%, demonstrating its effectiveness in processing time series data.

The application of the TFT in Bitcoin price prediction has emerged as a notable area of research in the broader context of ML and time series forecasting. In Amadeo et al. (2023), the TFT model is used for multi-step Bitcoin price prediction. Along with Bitcoin data from 2014–2020, additional inputs such as Twitter sentiment, trends, and seasonality are included in the model. The best-performing Method 4 outperformed the other models with an MAE of 0.05, RMSE of 0.07,

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MAPE of 5.92%, and quantitative missingness of 0.03, demonstrating a strong forecasting performance in Bitcoin's highly volatile market conditions. Khaniki and Manthouri (2024) used a transformer-based performer neural network and a BiLSTM (bidirectional LSTM) model to improve the price prediction of cryptocurrencies such as Bitcoin, Ethereum, and Litecoin. Technical indicators were added to capture momentum, volatility, and trends in the cryptocurrency markets. The Performer model improves computational efficiency thanks to the FAVOR+ mechanism, while BiLSTM improves forecast accuracy by processing temporal dynamics in the data in both directions. The model was tested on hourly and daily timeframes and showed the best performance compared to existing methods. In metrics such as RMSE, MSE, R-squared, and MSLE, the Performer + BiLSTM model achieved lower error rates, outperforming other models. In Penmetsa and Vemula's (2023) study, the LSTM and transformer models for cryptocurrency price prediction were tested in combination with momentum and volatility technical indicators. The study aimed to improve the accuracy of the models by using technical indicators such as RSI, Bollinger Bands %B, and MACD to predict Bitcoin, Ethereum, and Litecoin prices. The results revealed that the Transformer model with technical indicators outperformed all other models. The best results are MAE for BTC: 506.17, RMSE: 704.57, MAPE: 1.96%. Transformer models generally provided higher forecasting accuracy than LSTM, and the inclusion of technical indicators improved the performance of both models. Murray et al. (2023) compared ML, DL, and ensemble models for cryptocurrency price prediction. The study examined the performance of models such as ARIMA, kNN, SVR, Random Forest (RF), LSTM, GRU, TCN, and TFT using a dataset covering XRP, Bitcoin (BTC), Litecoin (LTC), Ethereum (ETH), and Monero (XMR) cryptocurrencies. The LSTM model provided the best results, with average RMSE: 0.0222, MAE: 0.0173, and MAPE: 3.86%. LSTM provided higher accuracy compared to the other models, especially since the performance of the ensemble models could not exceed that of the individual models.

2.2 | The Current Work

To summarize, many studies have been conducted on the impact of global variables on Bitcoin price forecasting. However, studies analyzing multiple global variables such as VIX, the oil price, DXY, the gold price, DGS5, and DFF simultaneously are limited. This study offers a more comprehensive approach by evaluating the impact of these variables on the Bitcoin price together. This will fill the gap in the literature in understanding the dynamics affecting Bitcoin's volatility, especially during periods of financial and economic crisis. ML and DL models have been extensively studied in the literature. However, there are limited studies on how well newer models such as TFT perform in Bitcoin price prediction compared to other widely used models such as LSTM and GRU. This study fills this gap by presenting a study that compares the TFT model with other models and evaluates its performance. Moreover, while many studies in the literature focus on specific periods, this study covers a long time period between 2012 and 2024. In this long time span, major events such as the COVID-19 pandemic, the Russia–Ukraine war, oil crises, etc. lead to complex and irregular data patterns in the Bitcoin price. Such large-scale events increase price volatility and complicate the performance of forecasting models. Therefore, this study takes these challenges into account and analyzes the impact of complex and long-term data patterns, focusing on achieving more robust and reliable results despite these factors that increase the difficulty of model forecasts. In this context, long-term event-based analysis and the application of models that are sensitive to complex data patterns will make an important contribution to address this gap in the literature. Another aspect of this comprehensive framework is to better understand the sensitivity of the Bitcoin price to major macroeconomic events and market dynamics. Recent studies have emphasized the linkages between cryptocurrency, equity and commodity markets. For instance, Akin et al. (2024) reveal the dynamic nature of the relationships between asset classes by analyzing fluctuations and correlated movements between these markets. Similarly, Akin et al. (2023) examine the impact of regulatory events on the Bitcoin price by analyzing how Bitcoin returns are affected by news about Centralized Digital Currencies (CBDCs) with the DCC-GARCH model. In light of these studies, the current study fills this important gap in the literature by analyzing the impact of macroeconomic variables and event-based factors on the Bitcoin price in a broader perspective. Moreover, the rolling window correlation analysis used shows that the relationship between Bitcoin and gold is not static, but changes over time. These findings are consistent with the theory of financial asset substitution and support that investors consider Bitcoin as a safe haven during periods of economic uncertainty. In this context, the application of long-term event-based analysis and models sensitive to complex data patterns will make a significant contribution to addressing this gap in the literature. In addition, ML and DL models are used in many studies in the literature, but hyperparameter optimization is generally limited. The use of advanced hyperparameter optimization methods such as Optuna and RandomSearchCV in our current study contributes to the literature by improving model performance. Accordingly, our study will fill an important gap in the literature in terms of both methodology and content and provide more comprehensive, reliable and advanced forecasting models for Bitcoin price forecasts.

3 | Methodology

3.1 | Data Set and Preprocessing

In this study, the time period between January 2012 and February 2024 is preferred because this period covers important turning points in Bitcoin's market history. In particular, factors such as the adoption of Bitcoin as a traditional investment instrument by institutional investors, global regulatory changes and macroeconomic events stand out as the main factors affecting price dynamics and volatility. The choice of this period makes it possible to study not only Bitcoin's price movements, but also fundamental changes in the market structure. For instance, the dramatic increase in the Bitcoin price during the COVID-19 pandemic in 2020 strengthened its perception as a safe-haven asset, in line with the macroeconomic effects of the pandemic. In contrast, regulatory interventions, such

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as China's mining ban in 2021, caused prices to fall. For these reasons, the study's choice of time period aims to provide a more comprehensive understanding of the dynamics in the Bitcoin price. The WTI-based oil price, the gold price, the US dollar index-based exchange rate, and the VIX were obtained from investing.com. The Market Yield on US Treasury Securities at 5-Year Constant Maturity and Federal Funds Rate were the basis for the interest rate, which was provided by the Federal Reserve Bank of St. Louis. In the data set, the Bitcoin price are used as the dependent variable and the global variables shown in Table 1 are used as independent variables.

The dataset includes these independent variables to understand how the Bitcoin price are affected under different macroeconomic conditions. The data set is divided into an 80% training set and a 20% test set. The training set is used to learn the models, while the test set is used to evaluate the performance of the models. It is important to normalize the variables in the data set in order to analyze the data at different scales together and to provide more reliable results of the models. However, it is also important which normalization method to choose. Financial time series are generally sensitive to outliers due to volatility and sudden market movements. Since the impact of outliers and the methods of dealing with them can directly affect model performance and generalizability, they are carefully considered at the data preprocessing stage. The analyses are performed using statistical methods. In the first step, outlier analysis was performed using the Z-Score method for the continuous variables in the data set (VIX, Oil, DXY, Gold, DGS5, DFF, and Bitcoin). Identifying outliers in data analysis is a critical aspect of statistical evaluation, especially when Z-scores are used as a method for detection. The Z-score indicates how many standard deviations away a data point is from the mean of the data set. In many statistical contexts, a Z-score greater than 3 or less than −3 is commonly used as a threshold for classifying a data point as an outlier. This rule is based on the properties of a normal distribution, where approximately 99.7% of data points lie within three standard deviations from the mean. Therefore, any data point that falls outside this range is considered statistically unusual and is usually flagged for further investigation (Al Sadi and Balachandran 2023). The results of the analysis using the Z-score method are shown in Table 2.

According to the results in Table 2, it is determined that there are outliers of 1.24% in the VIX variable, 0.03% in the Oil variable and 1.01% in the Bitcoin variable, while the outlier rates in other variables are at negligible levels. In Table 3, in order to evaluate whether the statistical properties of the data set are distorted due to outliers, the statistical properties of the entire data set, as well as the mean, standard deviation, minimum and maximum values of continuous variables when outliers are excluded, are recalculated and shown. The results obtained showed that the removal of outliers had a limited impact on the main trends and distribution of the data set. While the mean value of the Bitcoin variable was 11702.35 with outliers included, this value decreased by only 3.97% to 11237.80 when outliers were removed. Similarly, the standard deviations of the continuous variables changed only marginally.

In the light of these findings, the Min–Max scaling method was preferred for the normalization of the data set. Given that the

TABLE 2 | Z-score analysis and outlier analysis results.

Variables	Number of outliers values	Proportion of outliers values
VIX	38	1.2414%
Oil	1	0.0326%
DXY	0	0.0000%
Gold	0	0.0000%
DGS5	0	0.0000%
DFF	0	0.0000%
Bitcoin	31	1.0127%

TABLE 1 | Inventory of the independent variables analyzed in the data set and the dependent variable.

Kind	Variable	Variable name	Variable description
Independent variables	x_1	VIX (Volatility Index)	It is an index that reflects market volatility and investor sentiment.
	x_2	Oil price	It represents fluctuations in the global energy market.
	x_3	DXY (US Dollar Index)	It is an index that measures the strength of the US dollar against other major currencies.
	x_4	Gold price	Since Bitcoin is seen as digital gold, it represents the relationship between gold and the Bitcoin price.
	x_5	DGS5 (5-Year US Bond Yield)	The yield on US Treasuries reflects investors' risk perception and interest rate expectations.
	x_6	DFF (Federal Funds Effective Rate)	It represents the policy interest rate of the US Federal Reserve and influences economic growth and inflation expectations.
Dependent variable	y	Bitcoin price	Represents daily Bitcoin price in US dollars.

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TABLE 3 | Summary statistics of continuous variables with and without outliers.

Full data summary								
	Count	Mean	Std	Min	25%	50%	75%	Max
VIX	3061	17.74785	6.804658	9.14	13.31	15.96	20.42	82.69
Oil	3061	69.20057	22.30172	−37.63	50.56	66.85	89.36	123.7
DXY	3061	93.,55,992	8.072915	78.27	89.57	95.22	98.49	114.11
Gold	3061	1505.617	281.6743	1051.74	1259.76	1396.4	1773.49	2077
DGS5	3061	1.817847	1.072785	0.19	1.04	1.62	2.43	4.95
DFF	3061	1.131421	1.528498	0.04	0.09	0.33	1.7	5.33
Bitcoin	3061	11702.35	15704.52	4.3	380	4401.3	18851.3	67527.9
Without outliers summary								
	Count	**Mean**	**Std**	**Min**	**25%**	**50%**	**75%**	**Max**
VIX	2992	17.31826	5.461978	9.14	13.27	15.85	20.1425	38.15
Oil	2992	69.66982	21.92223	12.34	50.93	67.27	90.035	123.7
DXY	2992	93.4877	8.136705	78.27	89.115	95.185	98.3725	114.11
Gold	2992	1501.165	282.7494	1051.74	1257.64	1367.465	1771.92	2077
DGS5	2992	1.841516	1.072283	0.19	1.1	1.63	2.4825	4.95
DFF	2992	1.152142	1.538745	0.04	0.09	0.36	1.7	5.33
Bitcoin	2992	11237.81	15004.81	4.3	374.8	4011.05	17838.2	58771.3

proportion of outliers in the dataset is limited and that these outliers do not seriously distort the overall statistical properties of the dataset, this method was an appropriate choice in terms of model performance. The *Z*-score based outlier assessment method used in the analysis is provided as a reference in this study to support the transparency and accuracy of our methodology. Min-max scaling method is particularly effective in improving the performance of ML algorithms by converting features into the range between 0 and 1 (Li et al. 2021). Algorithms using gradient descent converge faster when data is normalized because the optimization environment becomes more manageable (Djordjević et al. 2022). Furthermore, min-max scaling helps to reduce the effects of outliers, but it should be noted that outliers can still affect the normalized output (Chimphlee and Chimphlee 2023). This technique, which is often preferred due to its simplicity and applicability, is faster than other normalization methods as it only requires minimum and maximum values (Elshewey et al. 2023).

$$x_{\text{scaled}} = \frac{x - x_{\min}}{x_{\max} - x_{\min}} \quad (1)$$

According to the correlation matrix presented in Figure 1, there are several correlations between the dependent variable, the Bitcoin price, and the independent variables. The strongest positive correlation is with gold at 0.71, indicating a strong positive relationship between the Bitcoin price and the gold price. The correlation between DXY and Bitcoin is 0.38, DGS5 is 0.31, and DFF is 0.25, indicating that these variables also have a positive impact on the Bitcoin price. On the other hand, weaker positive correlations were observed between VIX and Bitcoin at 0.23 and Oil at 0.12.

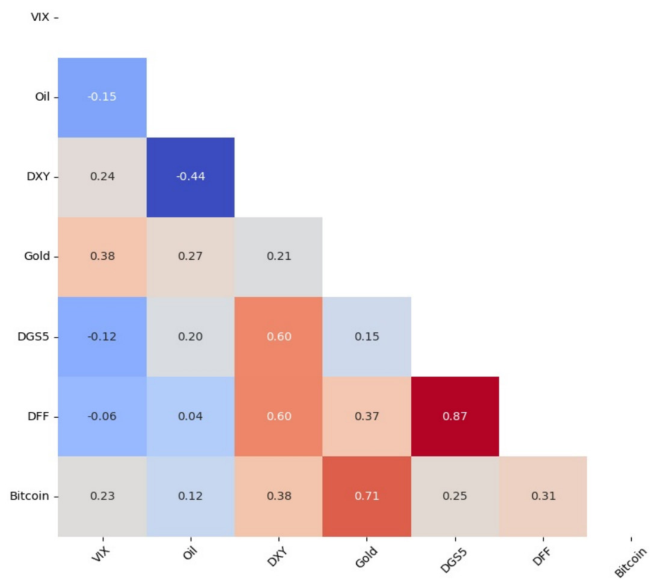

FIGURE 1 | Pearson's coefficient correlation matrix.

In particular, the effect of the gold variable on the Bitcoin price is more pronounced. These results provide an in-depth understanding of the relationships between the variables and identify possible economic models that can help predict the Bitcoin price.

According to the results of the correlation analysis, there is a high correlation between the Bitcoin and gold price. To gain a deeper understanding of the dynamics of the relationship

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between Bitcoin and gold prices over time, a rolling window correlation approach was used. While traditional correlation analyses usually measure a static relationship, this approach may be limited in dynamic and ever-changing systems such as financial markets. In order to overcome this shortcoming, sliding window correlation analysis allows for the detection of inter-period variations in time series relationships. This method helps to understand how the correlation between two assets is affected by macroeconomic conditions, market sentiment, regulatory changes and other exogenous factors. The different window sizes used in this analysis (30 and 90 days) allow to study short-term market fluctuations (30 days) and longer-term trends (90 days). Thus, one can assess the level of stability of the relationship between Bitcoin and gold and how different investor behaviors are shaped by changing market conditions. This analysis aims to evaluate the relationship between Bitcoin and gold, a traditional safe-haven asset, from a theoretical perspective and in the light of periodic changes. The ultimate goal of the analysis is not only to identify the relationship, but also to show how this relationship is shaped by economic, political and financial factors and to increase the analytical value of the study. Figure 2 shows the results of the analysis. The results reveal significant fluctuations in the correlation, ranging from positive to negative values, and highlight strong co-movement as well as periods of divergence. For instance, the 90-day window provides a smoother perspective on long-term trends, while the 30-day window provides a more detailed view of short-term volatility. These findings address the commentator's suggestion by showing how the Bitcoin-gold correlation is not static but changes over time, influenced by macroeconomic conditions, investor sentiment and market dynamics. Moreover, these results are consistent with theories of financial asset substitution, where assets such as gold and Bitcoin can change their role as safe-haven investments depending on the current economic climate. This dynamic approach enhances the analytical rigor and relevance of the study by highlighting the nuanced interaction between these two assets.

3.2 | Model Selection

To monitor the behavior of the variables in the data set over time, an analysis called decomposition was performed. Observed, trend, seasonal, and residual components are shown in Figure 3. According to the decomposition analysis in the figure, the Bitcoin price exhibits a very different dynamic compared to the independent variables VIX, Oil, DXY, Gold, DGS5, and DFF. The top left chart clearly shows that Bitcoin price series is much higher and more volatile than the other variables. The trend component chart on the top right shows that the Bitcoin price has been on a significant uptrend since 2017, with large fluctuations, especially after 2020. The seasonality component in the bottom left chart shows that Bitcoin has a recurring seasonal structure in certain periods, while the seasonality structure of other variables is weaker. The residual plot on the bottom right shows that unexplained volatility in the Bitcoin price is quite pronounced and that these residuals indicate large price fluctuations. Overall, it can be said that Bitcoin has a different structure in relation to the independent variables and has larger trend and seasonal components than the other variables analyzed. Since such complex and non-linear structures cannot be fully captured by classical statistical methods, more powerful models had to be used in Bitcoin price forecasting.

In this context, DL and ML-based models are preferred. LSTM, which is highly successful in capturing long-term dependencies in time series data, is an effective model for predicting data with high volatility and long-term trends such as Bitcoin (Deng et al. 2024). In the decomposition analysis, it is observed that Bitcoin shows large fluctuations, especially after 2017, and exhibits a complex trend structure. LSTM is preferred because it can successfully learn these long-term dependencies and complex data patterns (Ding et al. 2024). Similar to LSTM, GRU, which is effective on time series data, stands out with its lighter and faster structure. GRU is capable of learning long-term dependencies like LSTM but requires less computational power (Hong, Yan, and Chen 2022). This is why the GRU model was preferred for capturing short-term changes as well as seasonality and trends in the Bitcoin price. CNN, which is commonly used for image processing, was used to capture local patterns and patterns in time series data of the Bitcoin price. The architecture of CNNs designed for spatial data allows the detection of short-term fluctuations and volatilities, which are critical in analyzing temporal sequences and economic forecasting (Gao et al. 2023). In order to capture the short-term fluctuations and volatilities of the Bitcoin price and other global variables, CNN is chosen as a powerful tool to explore the temporal pattern of data. In particular, CNN can model recurrent patterns in the Bitcoin price by detecting seasonality and short-term patterns. The TFT model is an advanced AI model in time series forecasting and is highly effective in capturing trend and seasonality patterns in multidimensional data (Laborda, Ruano, and

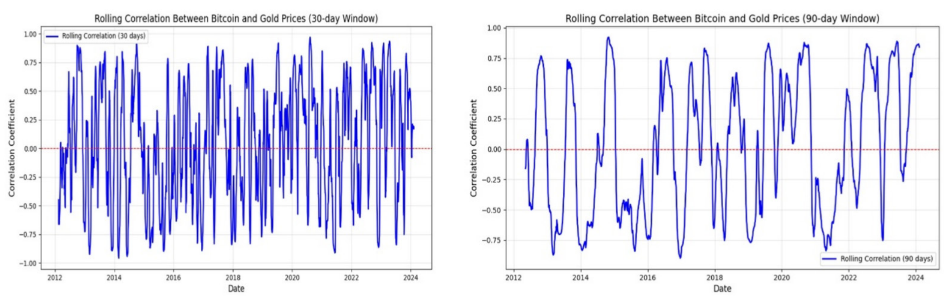

FIGURE 2 | Results of sliding window correlation analysis.

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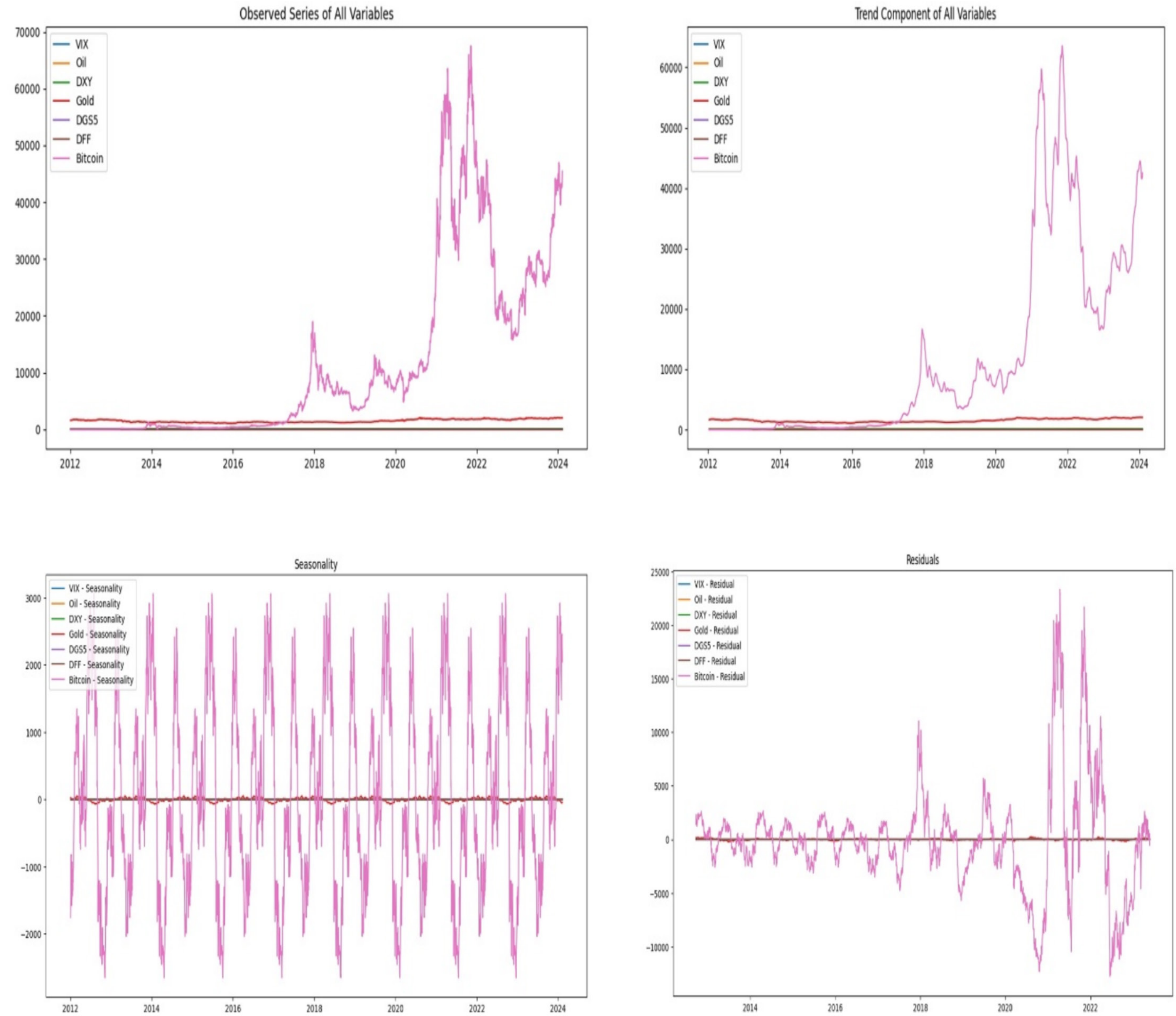

FIGURE 3 | Decomposition analysis results for all variables in the data set.

Zamanillo 2023). In particular, TFT was chosen to model the large fluctuations in the Bitcoin price and the complex relationships with independent variables. This model is thought to effectively capture seasonal patterns and trends in time series. One of the reasons for the choice of this model is that the TFT can examine the effect of each independent variable on the dependent variable over time separately, which provides an advantage in terms of explainability (Yun et al. 2023). This will allow it to more clearly reveal the impact of other analyzed variables on Bitcoin. On the other hand, XGBoost, a popular model among tree-based algorithms, is powerful in capturing non-linear relationships (Ainiwaer et al. 2023). It was chosen to model the complex interactions between the Bitcoin price and global variables such as VIX, Oil, DXY, Gold, DGS5, and DFF. XGBoost is also able to work effectively on large data sets due to its high speed and high accuracy (Liu et al. 2024). On the other hand, the LightGBM model has an advantage over other models, especially with its fast training time and low memory usage (Sari 2023). It is a model that provides fast and efficient results when working with large data sets and high-dimensional features (Choi, Choi, and Heo 2023). Considering the large fluctuations in Bitcoin's trend and seasonality components observed in the decomposition analysis and the non-linear relationships with other global variables, it is thought that the LightGBM will model these complex relationships effectively and provide a significant advantage in terms of processing the results quickly. Finally, the SVR model was preferred in the study as a particularly effective model for capturing complex nonlinear relationships (Fung, Huang, and Koo 2018). When we look at the decomposition analysis, it is observed that the Bitcoin price has much higher volatility compared to other independent variables and show large fluctuations, especially in the trend and seasonality components. Such complex and non-linear data structures are areas where models such as SVR are strong. SVR is effective in capturing subtle and sensitive relationships in the data and has the capacity to model unexplained volatility in the residuals in decomposition analysis (Xu et al. 2020). In cases where the Bitcoin price exhibits large fluctuations and these fluctuations cannot be fully explained, SVR's ability to

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learn nonlinear structures is preferred to better model these complex relationships.

3.3 | DL and ML Models

This section describes the DL and ML models used to predict the Bitcoin price. Each model has its own structure, data processing capacity and advantages. In the following subheadings, these models are introduced. ML and DL stand out as data-driven approaches that can provide powerful insights when working with large and complex data sets. While ML algorithms make predictions by identifying patterns in the data and discovering relationships, DL models offer a more effective solution, especially in learning complex and irregular patterns in time series data. The DL models used in this study, such as LSTM, GRU and TFT, are customized to understand the sequential nature of time series. In particular, the TFT model is designed to analyze the impact of both macroeconomic and event-based variables and can work well with the dummy variables used in this study. In this context, this study aims to improve both price forecasting performance and to better understand the impact of macroeconomic variables by combining ML and DL methods.

3.3.1 | LSTM

LSTM neural networks are a type of RNN architecture that is particularly successful in learning long-term dependencies in time series data (Kuang et al. 2022). LSTMs were developed to solve the vanishing gradient problem of ordinary RNNs. RNNs operate on sequential data over time but may fail to retain information over a long period of time. LSTMs overcome this problem, making it possible to learn longer-term dependencies (Kim, Yang, and Kim 2020). The basic building block of an LSTM is the cell, and each cell has three important gates. The input gate controls the entry of new information into the cell. Output gate controls how the cell state is transferred to the outside. The Forget gate determines how much of the previous cell state is retained (Ishida et al. 2021). Thanks to this mechanism, LSTMs have the ability to retain information from previous time steps for a long time and use this information when needed. These gates in the LSTM cell decide what information to keep and what information to forget during the relevant time period. An information pipeline, called cell state, enables information transportation. In this way, it efficiently preserves long-term information. The mathematical formulations of the forget gate, input gate, cell state update, new cell state update, and output gate in the LSTM cell are shown in Equations (2)–(7), respectively.

Forget Gate:

$$f_t = \sigma\left(W_f \cdot \left[h_{t-1}, x_t\right] + b_f\right) \tag{2}$$

where x_t is the input vector at the time slot. h_{t-1} is the previous cell output. W_f is the weight matrix for the forget gate. b_f is the bias term for the forget gate. σ is the sigmoid activation function.

Input Gate and cell status update:

$$i_t = \sigma\left(W_i \cdot \left[h_{t-1}, x_t\right] + b_i\right) \tag{3}$$

$$\widetilde{C}_t = \tanh\left(W_C \cdot \left[h_{t-1}, x_t\right] + b_C\right) \tag{4}$$

where i_t gives the decision of the entrance gate. $\widetilde{C}_t$ is the candidate vector for the new cell state. W_i is the weight matrix for the input gate. W_C is the weight matrix for the new cell state.

Cell State Update:

$$C_t = f_t \cdot C_{t-1} + i_t \cdot \widetilde{C}_t \tag{5}$$

These equations determine how much of the previous cell state is retained and how much of the new cell state candidate is added.

Output Gate:

$$o_t = \sigma\left(W_o \cdot \left[h_{t-1}, x_t\right] + b_o\right) \tag{6}$$

$$h_t = o_t \cdot \tanh\left(C_t\right) \tag{7}$$

The output gate determines the amount of information to be transferred out of the cell.

One of the most important advantages of LSTM is its ability to learn long-term dependencies. Unlike other recurrent networks, LSTMs minimize the problem of gradient fading and make the learning process more stable. It can also successfully model complex and long-term relationships in time series data. However, LSTMs are not without their drawbacks. Their complex structure makes the training process slower and requires more computational power. Moreover, optimization of LSTM in large data sets and long sequences can be difficult (Kuang et al. 2022).

3.3.2 | GRU

GRU is a variant of RNNs, a model that works particularly effectively in time series analysis and sequential data. Like LSTM, GRU is capable of learning long-term dependencies, but with a simpler structure. Thanks to this structure, GRU overcomes the vanishing gradient problem often encountered in RNNs and is more effective in learning long-term dependencies (Guerra et al. 2023). In GRU, there is no separate cell state as in LSTM; the cell state and output are combined. This makes GRU a faster and less computationally demanding model. GRU uses two gates in the cell structure: the update gate and the reset gate. The Update gate controls how much of the information in the cell is updated. The reset gate determines how much of the previous cell state is forgotten and controls how new information is inserted (Dong et al. 2023). The mathematical formulations of the GRU model are shown in Equations (8)–(11), respectively.

Update Gate:

$$z_t = \sigma\left(W_z \cdot \left[h_{t-1}, x_t\right] + b_z\right) \tag{8}$$

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where x_t is the input vector at the time step. h_{t-1} is the cell state at the previous time step. W_z is the weight matrix for the update gate. b_z is the bias term for the update gate. σ is the sigmoid activation function.

Reset Gate:

$$r_t = \sigma\left(W_r \cdot \left[h_{t-1}, x_t\right] + b_r\right) \tag{9}$$

where the reset gate determines how much of the previous cell state $h_{t-1}$is reset.

Candidate Cell State:

$$\widetilde{h}_t = \tanh\left(W_h \cdot \left[r_t \cdot h_{t-1}, x_t\right] + b_h\right) \tag{10}$$

In this step, the reset gate is used to determine how the previous cell state and the new input will be combined.

Final Cell State:

$$h_t = \left(1 - z_t\right) \cdot h_{t-1} + z_t \cdot \widetilde{h}_t \tag{11}$$

where the update gate z_t establishes a balance between the previous cell state h_{t-1} and the new cell state $\widetilde{h}_t$.

In addition to the advantages of GRUs, there are also some disadvantages. GRUs may not be able to model very complex and long-term dependencies as well as LSTM because they have fewer gates. Also, whereas in LSTM the entry, forget, and exit gates are each independent, in GRU these control mechanisms are more limited. This may reduce flexibility in some problems (Tutubalina and Nikolenko 2017).

3.3.3 | CNN

CNN is one of the DL methods, often used in tasks such as image recognition and processing. CNNs learn relationships in visual and sequential data by using convolution operations to learn local features in data (Wu et al. 2022). It can also be used in time series data to capture patterns in sequential data. While CNNs have revolutionized the field of image processing in particular, in addition, they have been adapted to work with one-dimensional time series data, allowing them to capture temporal dependencies while maintaining the advantages of convolutional operations (Farag 2022). The architecture of CNNs allows them to process data in parallel, which can lead to faster training times and better performance compared to traditional sequential models such as RNNs (Shang et al. 2023). CNNs usually consist of three basic layers: convolutional, pooling, and fully connected layers. The convolutional layer is the layer that extracts feature maps from the data and learns local patterns. In this layer, kernels are used to apply a sliding window to the data and learn the features in each region. The convolution process learns the relationship between the input data and the filter and is defined as shown in Equation (12):

$$(X * K)(i, j) = \sum_m \sum_n X(i + m, j + n) \cdot K(m, n) \tag{12}$$

where$X$ is the input data, K is the kernel, i, j is the location where the convolution process is applied. After the convolution layer, the ReLU (Rectified Linear Unit) activation function is usually applied. After activation, pooling is performed. For example, maximum pooling is the process of applying a window to each filter and taking the maximum value. This process is shown in Equation (13).

$$y = \max\left(x_1, x_2, \ldots, x_n\right) \tag{13}$$

This reduces the size and increases the information density by selecting the maximum value in each window. However, the feature maps are flattened to the fully connected layer and the final output generation for a classification or prediction problem is shown in Equation (14).

$$y = W \cdot x + b \tag{14}$$

where W represents the weight matrix, x represents the input vector, and b represents the bias term.

CNNs have the ability to learn local patterns in different regions of the data through filters. This provides an important advantage, especially in image and time series data. While traditional methods require manual feature extraction, CNNs can automatically learn features (Zafar et al. 2022). With the pooling layer and convolution process, the dimensions of the data are reduced and the number of parameters of the network is reduced, which reduces the computational cost (Kuzinkovas and Clement 2022). However, CNNs also have a number of disadvantages. CNNs generally work better with large data sets. The risk of overfitting is high with small data sets. Also, CNNs require high computational power when working with large-sized data and a large number of filters (Si et al. 2021). The deep structure of CNN leads to an increase in the number of parameters and the complexity of the model. This may require more time and resources for training the model (Zhong et al. 2023).

3.3.4 | TFT

TFT is a model for multivariate time series forecasting. Introduced in 2019 by Google, TFT was developed to model both short-term and long-term dependencies and can effectively learn both linear and non-linear relationships (Ye, Zhu, and Zhang 2024). TFT provides a flexible and powerful solution by utilizing attention mechanisms in time series analysis. Unlike traditional time series methods, the most important feature of TFT is its ability to learn global and local dependencies. This model is equipped with innovative mechanisms such as attribute-level attention mechanisms and temporal attention mechanisms (Santos et al. 2022).

The TFT consists of several basic components, each of which is customized for a different task. The Gated Residual Network (GRN) is used for processing inputs in a non-linear manner. This structure decides how to process data from the past using a gate mechanism for each input. This structure is shown in Equation (15).

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$$h = layerNorm\left(\mathrm{ReLU}\left(W_1 \cdot x + b_1\right) \cdot g + x\right) \tag{15}$$

where W_1 is the weight matrix, x is the input vector, g is the output of the gate mechanism, ReLU is the nonlinear activation function.

The TFT learns which information is more important at different time steps using a multiple attention mechanism. This process is illustrated in Equation (16).

$$Attention(Q, K, V) = Softmax\left(\frac{QK^T}{\sqrt{d_k}}\right)V \tag{16}$$

where Q is the query matrix, K is the key matrix, V is the value matrix, and d_k is the dimension of the matrices. This mechanism learns which attributes are more strongly associated with critical moments in the time series.

Static Covariate Encoders, however, are used to model fixed attributes. Static attributes are data that do not change over time. They are learned at the beginning of the model and incorporated into the model's estimation process, as shown in Equation (17).

$$h_{static} = GRN(static\_input) \tag{17}$$

A Temporal Decoder layer is used to make predictions from past and future time series data. This layer obtains more accurate predictions by modeling future events as shown in Equation (18).

$$y_{t+1} = Decoder\left(h_{past}, h_{future}\right) \tag{18}$$

where the past time series data h_{past} and the data on future events h_{future} are processed by the solver to make future predictions.

Despite its advantages, the TFT model is not without limitations. Due to its complexity, TFT requires high computational power in the training and prediction process. This can increase the processing time for large data sets (Luo et al. 2024). Although TFT is a powerful model, it may carry the risk of overfitting on small data sets. Therefore, it works more effectively with large and rich data sets (Laborda, Ruano, and Zamanillo 2023). The components of the TFT are more complex than other time series models. This can make it difficult to optimize the model and may require more expertise (Samimi et al. 2022).

3.3.5 | Extreme Gradient Boosting (XGBoosting)

XGBoost is a ML algorithm based on decision trees and is known for its high performance, especially in classification and regression problems. XGBoost is a derivative of gradient boosting and incorporates several improvements to increase accuracy and optimize computational efficiency. This algorithm produces fast and accurate results on large data sets and provides better generalization with features such as regularization, learning rate, and combination of weak learners (Octavianto and Wibowo 2024). Boosting is a method of sequentially training weak learners (usually decision trees), where each new tree corrects the errors of the previous trees. XGBoost uses gradient descent to minimize the residuals at each step (Panjee and Amornsawadwatana 2024).

XGBoost expresses the predicted value as $\hat{y}_i$ and the loss function is as shown in Equation (19) with y_i being the true value:

$$L\left(\hat{y}_i, y_i\right) = \sum_{i=1}^{n} \ell\left(y_i, \hat{y}_i\right) + \sum_{k=1}^{K} \Omega\left(f_k\right) \tag{19}$$

where $\ell\left(y_i, \hat{y}_i\right)$ is the loss function (e.g., MSE or log-loss). $\Omega\left(f_k\right)$ is the regularization term and prevents overfitting by penalizing the complexity of the model. k is the decision tree.

At each step, the gradient descent is calculated as shown in Equation (20) based on the errors in the predictions of the previous step:

$$\hat{y}_i^{(t+1)} = \hat{y}_i^{\,t} + \eta \cdot f_t\left(x_i\right) \tag{20}$$

where $\hat{y}_i^{\,t}$ is the prediction made at the tth step. η is the learning rate and determines how fast the model is updated at each step. $f_t\left(x_i\right)$ is the$t$th decision tree.

In addition to its advantages, the XGBoost model also has disadvantages. Although the model performs strongly on large data sets, it can be overly complex and time-consuming on small data sets (Guo and Zhang 2024). On the other hand, for XGBoost to perform well, the hyperparameters need to be carefully tuned (Gono, Napitupulu, and Firdaniza 2023). Incorrect tuning can cause the model to overlearn or underperform. Model explainability is especially challenging in large models with a large number of decision trees.

3.3.6 | Light Gradient Boosting Machine (LightGBM)

LightGBM is a gradient-boosting algorithm developed by Microsoft that works quickly and efficiently on large data sets. LightGBM is used to solve classification and regression problems, especially based on decision trees, and is highly efficient in terms of performance. Similar to XGBoost, it combines gradient boosting with weak learners, but with significant advantages such as faster training and lower memory consumption (Wang et al. 2023). The main difference of LightGBM is the way it categorizes and grows data points. Unlike standard gradient boosting algorithms, LightGBM uses a histogram-based learning algorithm and grows the tree structure vertically instead of horizontally. This significantly speeds up the way the data is processed and results in less resource consumption (Yürekli et al. 2022). In LightGBM, each prediction $\hat{y}_i$ is calculated as shown in Equation (21):

$$\hat{y}_i^{(t)} = \hat{y}_i^{(t-1)} + \eta f_t\left(x_i\right) \tag{21}$$

where $\hat{y}_i^{(t)}$ is the prediction made at the tth iteration. $f_t\left(x_i\right)$ is the tth decision tree. η is the learning rate and determines how much the model is updated at each step.

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LightGBM minimizes an error function at each iteration. The loss function L is as shown in Equation (22):

$$L(\hat{y}_i, y_i) = \sum_{i=1}^{n} \ell(y_i, \hat{y}_i) + \sum_{k=1}^{K} \Omega(f_k) \tag{22}$$

where $\ell(y_i, \hat{y}_i)$ is the loss function (e.g., MSE or log-loss). $\Omega(f_k)$ is the regularization term and prevents overfitting by penalizing the complexity of the model. k is the decision tree.

In addition to its advantages, it also has disadvantages. LightGBM can generate very deep trees due to its leaf-based growth strategy. This can lead to overlearning and reduce the generalization ability of the model (Kulkarni 2022). In small datasets, LightGBM can sometimes overlearn, which can reduce the generalization ability of the model. It also requires careful hyperparameter tuning to perform correctly (Manikandaraja, Aaby, and Pitropakis 2023). Improper tuning of hyperparameters can seriously affect the performance of the model.

3.3.7 | SVR

SVR is an adaptation of the Support Vector Machine (SVM) algorithm to regression problems. SVM is typically used for classification problems, while SVR is used for the prediction of continuous variables. SVR performs strongly on nonlinear and linear regression problems and can also be used in time series analysis. Its basic principle is to minimize errors by penalizing data points that fall outside the errors while ensuring that most of the predicted values are within an epsilon margin (Dai et al. 2022). SVR tries to find a linear hyperplane (or a decision boundary for non-linear cases) to predict the target variable. Like SVM, it ensures that most of the data points stay within a margin and focuses only on data points outside the margin. A penalty term is applied for data points that fall outside the margin. The most important feature of SVR is that it ignores small errors using an epsilon-insensitive loss function and uses a penalizing function for larger errors (Sifaou, kammoun, and Alouini 2021).

SVR learns a function $f(x)$ to predict the target. This function is expressed as shown in Equation (23):

$$f(x) = w^T \cdot x + b \tag{23}$$

where w represents the weight vector, x represents the input, b represents the bias term. SVR optimizes the errors in the margin and the penalty term. The model minimizes the errors $y_i - f(x_i)$ but ignores errors up to a given value ϵ. Furthermore, a penalty is applied for errors outside the margin. The loss function is as in Equation (24):

$$L(y_i, f(x_i)) = \max(0, \left| y_i - f(x_i) \right| - \epsilon \tag{24}$$

This function is optimized by penalizing errors that exceed the tolerance ε. The aim is to accept all predictions that fall within a tube of width ε and penalize errors outside the tube. The optimization problem of the SVR is expressed as in Equation (25):

$$min_{w,b,\xi} \frac{1}{2} \|w\|^2 + C \sum_{i=1}^{n} (\xi_i + \xi_i^*) \tag{25}$$

where $\frac{1}{2}\|w\|^2$ is the term used to adjust the weights of the model. $\xi_i$and ξ_i^* are penalty terms for positive and negative errors that fall outside the margin. C is the penalty coefficient and determines how much error the model can make. SVR also offers a more flexible structure by using kernel functions on non-linear data. The most common linear kernel, radial basis function (RBF), and polynomial kernel functions are shown in Equations (26)–(28), respectively.

$$K(x_i, x_j) = x_i^T x_j \tag{26}$$

$$K(x_i, x_j) = \exp\left(-\gamma \left\| x_i - x_j \right\|^2 \right) \tag{27}$$

$$K(x_i, x_j) = (x_i^T x_j + c)^d \tag{28}$$

Besides its advantages, SVR also has some disadvantages. The training time of SVR increases significantly as the dataset size increases, which can cause performance problems with large datasets. For SVR to work correctly, its hyperparameters need to be carefully tuned. Incorrect settings can negatively affect the performance of the model. The decision boundaries generated by SVR with kernel functions are often complex and make the model difficult to interpret (Utomo and Nugroho 2022).

3.4 | Software and Hardware

In this study, DL and ML models were developed using Python v11 programming language. The analysis processes were carried out in Jupyter Notebook, an interactive data processing environment. DL models such as LSTM, GRU, and CNN were developed using TensorFlow and Keras libraries, while Scikit-learn was used for ML models such as XGBoost, LightGBM and SVR. Performance optimization of XGBoost and LightGBM models was achieved with the relevant libraries. Optuna was used for hyperparameter optimization of DL models and PyTorch was used for the development of the TFT model. The model training and testing processes were carried out on a computer with AMD Ryzen 53,600 processor, 16 GB RAM and AMD Radeon RX 5700 XT graphics card using Windows 11 Pro operating system, which enabled fast processing of large data sets.

3.5 | Performance Evaluation Metrics

The performance of the machine and DL models used in the study was measured by R^2, MAE, MAPE, MSE, and RMSE metrics. R^2 indicates the proportion of variability that the model can explain and a value close to 1 indicates high accuracy (Ibrahim and Singh 2022). MAE measures bias by averaging the absolute differences between actual and predicted values (Fakharchian 2023). MAPE presents these differences in percentages and is used to assess prediction accuracy (Shen 2022). MSE gives the mean of the squares of the errors and emphasizes the impact of large errors (Wen and Ling 2023), while RMSE presents the magnitude of error as the square root of MSE on a comprehensible scale (Fakharchian 2023). These metrics allow assessing the accuracy of predictions from different

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perspectives. The mathematical formulations of these metrics are shown in Equations (29)–(33), respectively.

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(y_i - \bar{y})^2} \tag{29}$$

$$\text{MAE} = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i| \tag{30}$$

$$\text{MAPE} = \frac{100\,\%}{n}\sum_{i=1}^{n}\left|\frac{y_i - \hat{y}_i}{y_i}\right| \tag{31}$$

$$\text{MSE} = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2 \tag{32}$$

$$\text{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2} \tag{33}$$

3.6 | Proposed Methodology

In this study, DL (LSTM, GRU, CNN, and TFT), ML (XGBoost, LightGBM, and SVR) algorithms and traditional econometric models (ARIMA, VARX, and GARCH) are applied to determine the best forecasting model using Bitcoin price and global indicators for the period 2012–2024. The data was normalized with Min-Max scaling and then divided into training and test sets. The training set is given as input to the models, and the test set is used to evaluate the prediction performance of the models. Furthermore, *k*-fold cross-validation was applied to test the generalization capacity of the models after these procedures. Optuna and RandomSearchCV methods were used for training and optimization of the models, and the test and cross-validation performances were evaluated with metrics such as R^2, MAE, MAPE, MSE, and RMSE. The main objective is to find the most successful prediction model by modeling nonlinear relationships in the best way. Then, once the most successful model is identified, we aim to analyze the decision-making processes behind this model. We examine which variables are more important for the model with the best prediction performance and discuss the role of these variables in Bitcoin price prediction in more detail. The proposed methodology is shown in Figure 4.

4 | Findings

4.1 | Findings From Traditional Econometrics, DL and ML

In this section, we will first present the best hyperparameter settings for DL and ML models determined by Optuna and RandomSearchCV optimization techniques and then analyze the performance results of the models in detail. In addition to DL and ML models, the inclusion of traditional econometric models will provide a benchmark to assess the added value of complex ML/DL models in forecasting the Bitcoin price. In order to clearly demonstrate the added value of ML/DL models in time series forecasting, traditional econometric models are also included in the study. ARIMA, one of the traditional econometric models, was used in the study. Auto-ARIMA was used to determine the optimal hyperparameters of the ARIMA model and Auto-ARIMA was used to determine the hyperparameters of the model. For the GARCH model, which is another econometric model used in this study, the Grid Search method is applied for optimal hyperparameter adjustment. Finally, for the VARX model, Akaike Information Criterion (AIC) was used to determine the appropriate number of lags for the model. The VAR model was applied on the training data and the optimal number of lags was selected after the evaluation up to a maximum of 15 lags. The hyperparameter settings determined by these optimization techniques to obtain the best performance from each ML and DL model are shown in Figure 5 below.

The Optuna method was used for hyperparameter optimization of DL models. Optuna creates a search space for optimizing the hyperparameters to determine the most appropriate hyperparameters for the model. In Optuna, hyperparameters are randomly selected within the ranges specified by the user. For instance, hyperparameters such as *units* (between 50 and 200), *learning rate* (between 1e−4 and 1e−1 on a logarithmic scale), *epochs* (between 50 and 200), and *batch size* (between 16 and 64) are suggested by Optuna. In this process, DL models were created using the proposed hyperparameters for each trial of the model and trained on the training set. During training, 20% of the data was reserved for validation with the parameter "validation_split = 0.2," and Optuna's "KerasPruningCallback" function helped to optimize the model according to the validation loss. The performance of the models was evaluated on the test set, and the "score" metric was returned. This process was repeated for 50 trials (*n_trials = 50*) with the "study. Optimize" function, and the hyperparameters of the model with the lowest error were determined. The RandomSearchCV method used in ML models plays an important role for hyperparameter optimization. In ML models, 100 different hyperparameter combinations were randomly selected and tested over predefined parameter ranges. The "RandomSearchCV" function evaluated the performance of the model using the negative mean square error metric. In this process, the model was tested with five-fold cross-validation (*cv = 5*). During optimization, processing time was reduced by using all processors with the parameter "n_jobs = −1," and reproducibility of the results was ensured with "random_state = 42". Table 4 shows in detail the ranges of hyperparameters optimized for each algorithm used in the study and the final optimal values obtained.

These details not only strengthen the reliability of the reported findings, but also provide a valuable reference for future studies using similar methods. In addition, the training, testing, and cross-validation performances of each model were evaluated using metrics such as R^2, MAE, MAPE, MSE, and RMSE. The metric results obtained from the training, testing, and cross-validation sets for traditional econometric models, DL and ML models are shown in Table 5.

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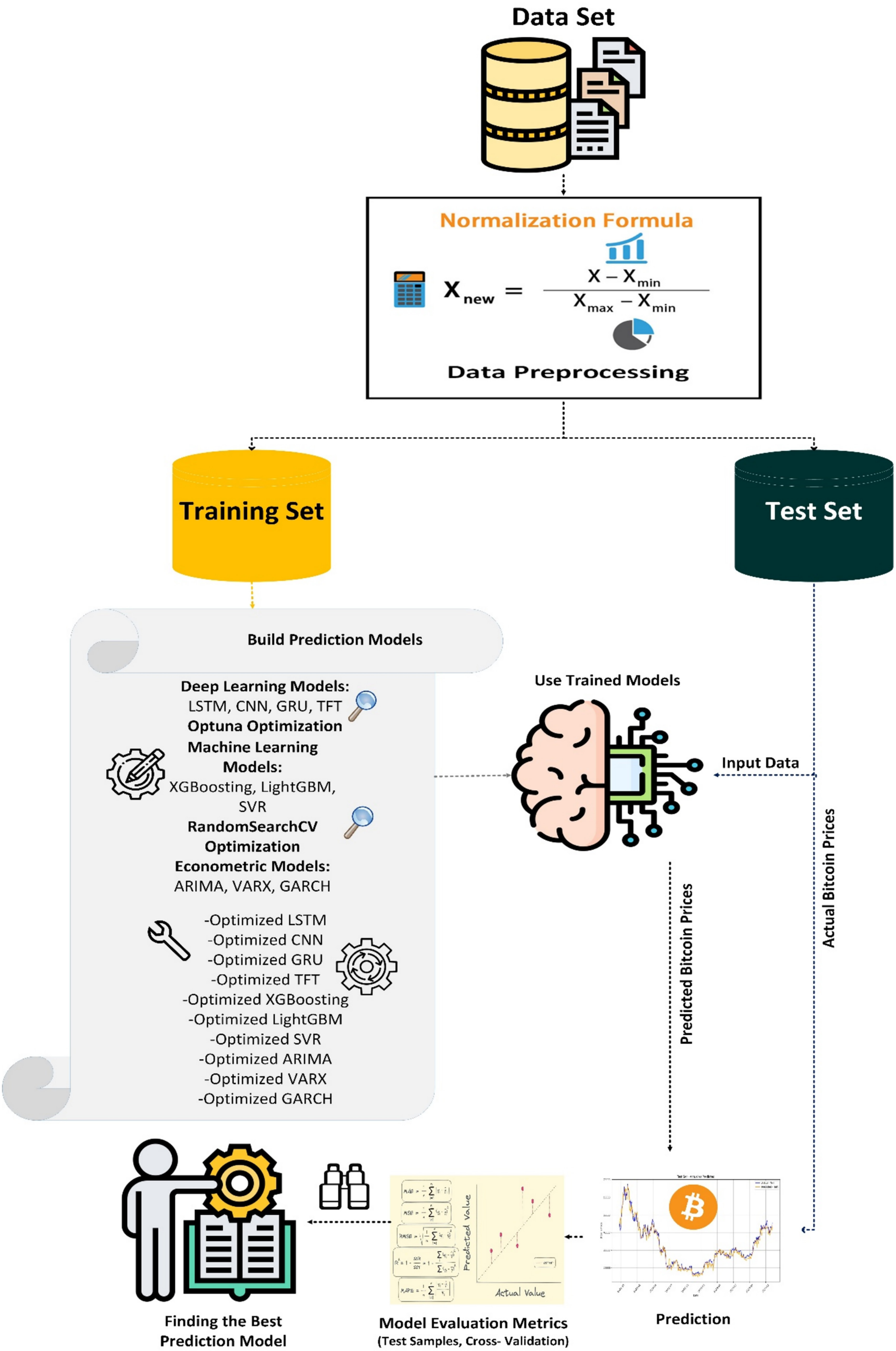

FIGURE 4 | Proposed methodology.

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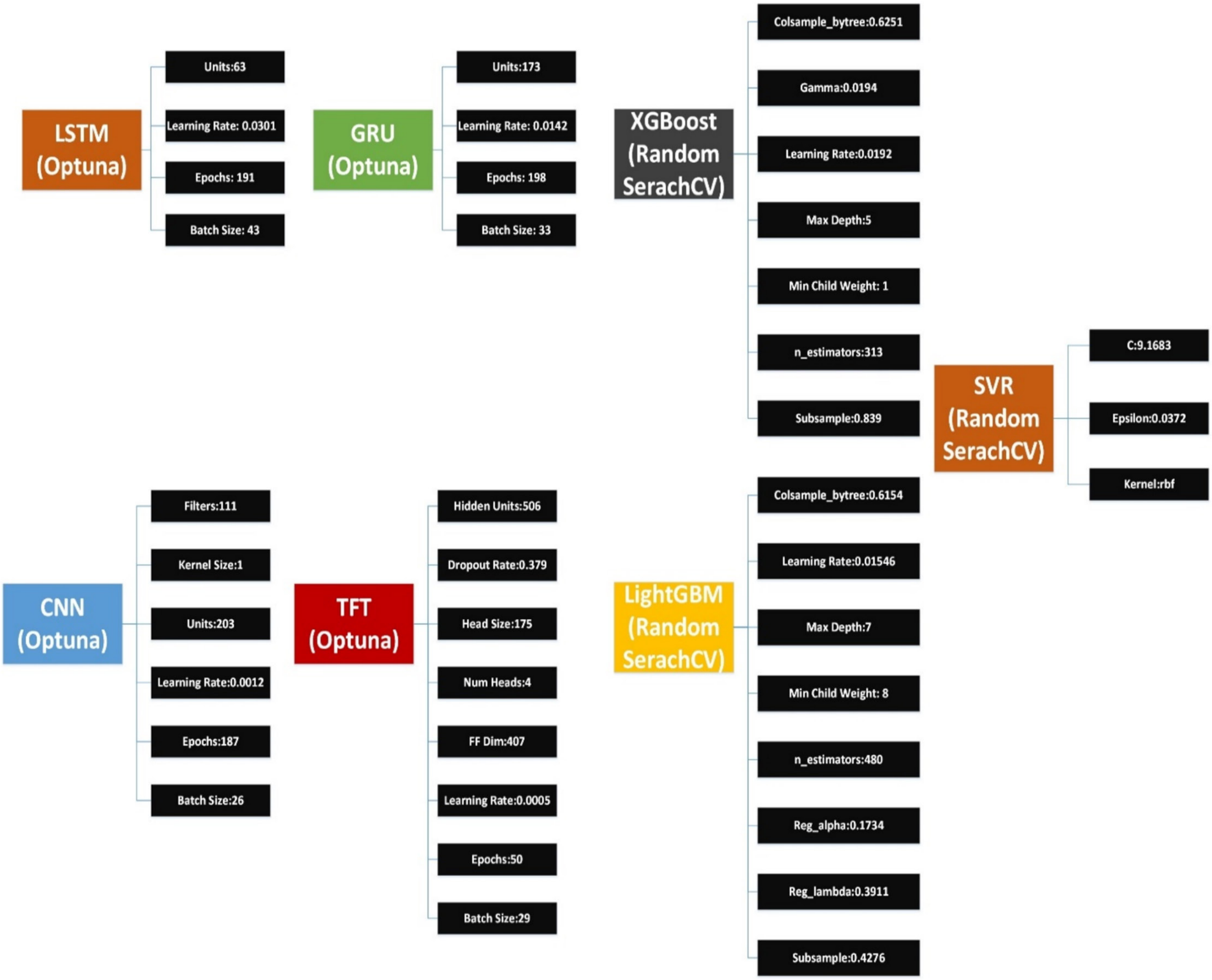

FIGURE 5 | Hyperparameter settings of DL and ML models determined by Optuna and RandomSearchCV Techniques.

The results shown in Table 5 compare the performance of different models on training, test, and 5-fold cross-validation sets using various metrics. In general, DL models (LSTM, GRU, CNN, and TFT) perform better than ML models (XGBoost, LightGBM, and SVR). The TFT model is particularly notable for its high R^2 scores and low error metrics (MAE, MAPE, MSE, and RMSE) in all sets, with an R^2 of 99.35% in the training set and an accuracy of 99.04% in the test set. The CNN model also performs well, standing out in the cross-validation phase with an R^2 of 99.08% and an RMSE of 0.0211. Although the LSTM and GRU models exhibit similar accuracy and error rates, the LSTM model achieved slightly better results than GRU in the test and cross-validation results. Looking at the ML models, the LightGBM model performs the best with an R^2 of 99.61%, especially on the training set, but lags behind the DL models in the test and cross-validation results. The XGBoost model performed poorly compared to the other models with low R^2 and high MAPE values, especially in the test and cross-validation sets. The SVR model, despite its ability to capture non-linear relationships, performed worse than the other models in the test and cross-validation phases; it had the highest error rates with an R^2 of 96.04% and MAPE of 21.99% in the test set. As a result, it is clearly seen that TFT, one of the DL models, is more successful in terms of accuracy in Bitcoin price predictions compared to other DL models and ML models. Furthermore, the results show that traditional econometric models (ARIMA, VARX, and GARCH) significantly underperform DL (LSTM, GRU, CNN, and TFT) and ML (XGBoost, LightGBM, and SVR) models. ARIMA, VARX, and GARCH models were found to have limited predictive power with negative R^2 values and high MAE and MAPE ratios. On the contrary, DL and ML models clearly outperformed with higher R^2 values (e.g., $R^2=0.9934$ for TFT), lower error rates (MAE and MAPE), and better generalization performance. In particular, DL models such as TFT and CNN produced the best results due to their ability to capture non-linear relationships and effectively model time series dynamics. These results clearly demonstrate the great value of ML and DL models over traditional methods in complex data structures. In the training process of the TFT model, the figure showing the loss values at each epoch is shown in Figure 6.

In the figure, the loss value of the TFT model starts quite high in the first few epochs and decreases rapidly. After about epoch 5, the loss value decreases to almost zero and maintains this low level throughout the model training. This shows that the model quickly minimizes the errors early in the training process and

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TABLE 4 | Hyperparameter ranges and optimal values for algorithms used in the study.

Model	Hyperparameters	Determined range/values	Optimal value
LSTM	Units	[50, 200]	63
	Learning rate	[0.0001, 0.04]	0.0301
	Epochs	[50, 200]	131
	Batch size	[16, 64]	43
GRU	Units	[50, 200]	173
	Learning rate	[0.0001, 0.01]	0.0142
	Epochs	[50, 200]	198
	Batch size	[16, 64]	33
CNN	Filters	[16, 128]	111
	Kernel size	[1, 7]	1
	Units	[100, 300]	203
	Learning rate	[0.0001, 0.01]	0.0012
	Epochs	[50, 200]	187
	Batch size	[16, 64]	26
TFT	Hidden units	[128, 512]	506
	Dropout rate	[0.0, 0.5]	0.379
	Head size	[32, 256]	175
	Num heads	[2, 8]	4
	FF dim	[128, 512]	407
	Learning rate	[0.0001, 0.01]	0.0005
	Epochs	[50, 200]	50
	Batch size	[16, 64]	29
LightGBM	Learning rate	[0.01, 0.3]	0.01546
	Max depth	[3, 10]	7
	Colsample bytree	[0.5, 1.0]	0.6154
	Min child weight	[1, 10]	8
	N estimators	[100, 500]	480
	Reg alpha	[0.0, 1.0]	0.1734
	Reg lambda	[0.0, 1.0]	0.3911
	Subsample	[0.5, 1.0]	0.4276
XGBoost	Colsample bytree	[0.5, 1.0]	0.6251
	Gamma	[0.0, 0.1]	0.0194
	Learning rate	[0.01, 0.2]	0.0192
	Max depth	[3, 10]	5
	Min child weight	[1, 10]	1
	N estimators	[100, 500]	313
	Subsample	[0.5, 1.0]	0.839
SVR	C	[1.0, 10.0]	9.1683

(Continues)

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TABLE 4 | (Continued)

Model	Hyperparameters	Determined range/values	Optimal value
	Epsilon	[0.01, 0.1]	0.0372
	Kernel	{"linear," "poly," "rbf," "sigmoid"}	"rbf"
ARIMA	AR: auto-regressive term (p)	$p=[0,5]$	4
	Difference term (d)	$d=[0,2]$	0
	MA: moving average term (q)	$q=[0,5]$	1
	Intercept	Adds a constant term to the model.	ARIMA(4, 0, 1) (with intercept) AIC Değeri: −260.628
VARX	Optimal lag	Optimal lag searched up to 15	Lag: 1, Parameters: 8, AIC: 1.0619, BIC: 1.2215, HQIC: 1.1206
GARCH	GARCH autoregressive term (p)	$p=[1,2,3]$	1
	GARCH moving average term (q)	$q=[1,2,3]$	1

fits the training data quite well after about epoch 5. The model does not show any signs of overfitting in the later epochs because the loss value remains constant, indicating that the training process does not tend to overlearn. Therefore, this kind of loss plot indicates that the learning rate of the TFT model is sufficiently tuned and the model is quickly optimized during training. On the other hand, the training and test set prediction graph of the TFT model is shown in Figure 7.

Analyzing the Bitcoin price prediction performance of the TFT model on both the training and test sets, the agreement between the model's predictions (orange) and the actual Bitcoin price (blue) is very high in the training set. Especially in the early periods when the Bitcoin price was stable, the model made very accurate predictions. After 2020, the model successfully captured the general trends and price movements, even during the period of sudden price spikes and fluctuations. In the training set, it is observed that the model works with great accuracy, and the training gives successful results on the model. Similarly, the figure of the test set shows that the model makes successful predictions. The agreement between actual and predicted prices is high, and the model captures short-term movements particularly well. However, it can be observed that the model's prediction errors increase relatively for some large price changes, but, in general, the model predicts future price movements with reasonable accuracy. In conclusion, the TFT model performed well in Bitcoin price predictions. In both the training and test sets, the model was able to accurately capture most of the price movements. The more precise results in the training set indicate that the model fits the data quite well, while the results in the test set show that the generalization capacity of the model is strong.

In addition, Figure 8 shows the importance scores of the global indicators used by the TFT model in forecasting in the test set based on the model's attention mechanism. The main purpose of the importance ranking based on the attention mechanism is to examine which variables the model gives more weight to and the impact of these variables on the forecasts. This analysis helps to understand which factors influence the model's decisions the most, especially in complex data sets with multiple attributes. In financial forecasts that are sensitive to global indicators, such as Bitcoin, this type of analysis reveals which economic factors are more decisive for the model's price movements. This information allows researchers and investors to better understand how the model works and better interpret the results by identifying the most important economic indicators. It is also important for the explainability of the model, as this mechanism ensures that the model's decisions are understood and validated, which increases credibility.

In the figure, the highest attention score is given to the Gold variable with 0.8497. This shows that gold is the most decisive factor in predicting the Bitcoin price compared to all other variables. Gold plays an important role during periods of inflation and other economic uncertainty, as it has historically been seen as a safe-haven asset. This explains why Gold is given such a high level of importance by the model. The second highest attention score is given to the DXY with 0.5211. The DXY represents the strength of the US dollar against other currencies and is directly related to global economic stability. This high level of attention is meaningful as the strength of the dollar can affect the demand for alternative assets such as Bitcoin. The DFF variable ranks third with an attention score of 0.4792, reflecting the interest rate policies of the US Federal Reserve. Interest rates have a significant impact on overall economic activity, which can indirectly affect the price of speculative assets such as Bitcoin. DGS5 has a moderate impact with an attention score of 0.3708. These bond yields reflect long-term economic expectations and inflation forecasts, which can affect the future performance of assets like Bitcoin. The VIX has a caution score of 0.3357, with a slightly more limited impact on volatile assets like Bitcoin. As the VIX index indicates general market uncertainty, it may contribute to Bitcoin price fluctuations during periods of risk aversion. Finally, the Oil variable has the lowest attention score of 0.2113. This suggests that the indirect impact of changes in the oil price on the Bitcoin price is limited. Bitcoin is perceived as an asset independent of global energy costs, which explains the low importance of oil. In conclusion, the attention mechanism of the TFT model reveals that the most influential variable on the Bitcoin price is gold, while other global factors are also influential to some extent. The model

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TABLE 5 | Performance metric results for training, testing, and cross-validation of all models.

Model	Set	R^2	MAE	MAPE	MSE	RMSE
LSTM	Training	0.9857	0.0178	4.1962	0.0007	0.0273
	Test	0.9854	0.0184	4.7707	0.0008	0.0295
	5-fold cross-validation	0.9821	0.0178	5.6409	0.0009	0.0303
GRU	Training	0.9833	0.0183	5.2075	0.0008	0.0295
	Test	0.9830	0.0189	6.5649	0.0010	0.0318
	5-fold cross-validation	0.9869	0.0158	6.0878	0.0006	0.0259
CNN	Training	0.9882	0.0167	3.4173	0.0006	0.0248
	Test	0.9872	0.0175	4.2348	0.0007	0.0276
	5-fold cross-validation	0.9908	0.0114	3.5231	0.0004	0.0211
TFT	**Training**	**0.9935**	**0.0119**	**3.2121**	**0.0003**	**0.0183**
	Test	**0.9904**	**0.0151**	**3.8763**	**0.0005**	**0.0238**
	5-fold cross-validation	**0.9934**	**0.0110**	**2.7582**	**0.0003**	**0.0184**
XGBoost	Training	0.9838	0.0177	14.4682	0.0008	0.0291
	Test	0.9776	0.0210	20.2134	0.0013	0.0365
	5-fold cross-validation	0.9678	0.0211	7.7631	0.0017	0.0418
LightGBM	Training	0.9961	0.0083	4.4442	0.0002	0.0141
	Test	0.9897	0.0129	5.3958	0.0006	0.0246
	5-fold cross-validation	0.9760	0.0146	3.4251	0.0013	0.0361
SVR	Training	0.9616	0.0287	18.4373	0.0020	0.0449
	Test	0.9604	0.0306	21.9978	0.0023	0.0486
	5-fold cross-validation	0.9555	0.0303	19.8294	0.0023	0.0482
ARIMA	Training	0.0057	0.1806	150.3124	0.0523	0.2287
	Test	−0.0006	0.1916	173.4094	0.0598	0.2445
	5-fold cross-validation	−0.0059	0.1814	151.3804	0.0527	0.2293
VARX	Training	0.0029	0.1807	150.9787	0.0525	0.2291
	Test	−0.0004	0.1906	171.1012	0.0473	0.2376
	5-fold cross-validation	−0.0032	0.1665	142.636	0.0489	0.1548
GARCH	Training	−0.0620	0.2061	201.4863	0.0559	0.2364
	Test	−0.2591	0.1684	52.8607	0.0752	0.2743
	5-fold cross-validation	−0.2732	0.1614	46.1984	0.0669	0.2582

takes into account a complex set of variables in predicting the Bitcoin price, but the influence of some variables is more dominant than others. However, Figure 9 shows how the attention mechanism scores for global variables change over time in the test set forecasts of the TFT model and how these changes react to global events. The attention scores in the figure represent the extent to which the model attaches importance to which variables in its forecasts in the relevant periods.

Figure 9 shows that the VIX and DXY attention scores increased during the period when the lasting effects of the COVID-19 pandemic on the global economy continued. Post-pandemic uncertainties may have increased market volatility and exchange rate volatility, leading the model to assign more importance to these variables. On the other hand, the attention scores of the DXY and Gold variables increased during the period when supply chain disruptions had a global impact. Supply chain disruptions led to inflationary pressures and increased the demand for safe haven assets such as gold. The importance of the dollar in this period can be attributed to the central role of the dollar in global trade. During the outbreak of the Russian–Ukrainian war, oil and the DXY increased significantly. The oil price rose due to supply constraints caused by the war, which also affected global economic balances. The safe-haven role of the dollar

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during the war also increased the importance of DXY in the model. However, when inflation became a global problem and central banks changed their monetary policies, the VIX, DFF, and gold attention scores increased. Rising inflation increased uncertainty in the markets and led central banks to adopt tightening monetary policies. This has led to assets such as gold gaining more importance. In the period when climate-related global events became more prominent, more stable and longer-term economic indicators such as the DFF and DGS5 started to gain importance. This shows that the long-term economic impacts associated with climate change are increasingly being taken into account in the markets and that such variables are gaining importance.

Gold featured prominently in the model with a high attention score, especially during periods of war and inflation. Gold's role as a safe haven has increased the sensitivity of the model to this variable. However, its importance has decreased in recent periods. Although oil has gained considerable importance during the war period, it has a low attention score in the overall trend. This suggests that the oil price is influential in certain periods but play a more limited role in the overall performance of the model. The DXY has attracted attention in the model as an important factor both during global economic uncertainty and during the war period. The role of the DXY as a global reserve currency was consistently taken into account by the model. The VIX was one of the variables that the model paid the most attention to during periods of uncertainty, but this attention decreased over time. This can be explained by the decline in market uncertainty. DFF and DGS5, as more stable economic indicators, increased their attention scores throughout the figure and stood out during the inflation policy period. Especially long-term economic expectations and central bank policies have increased the importance of these variables.

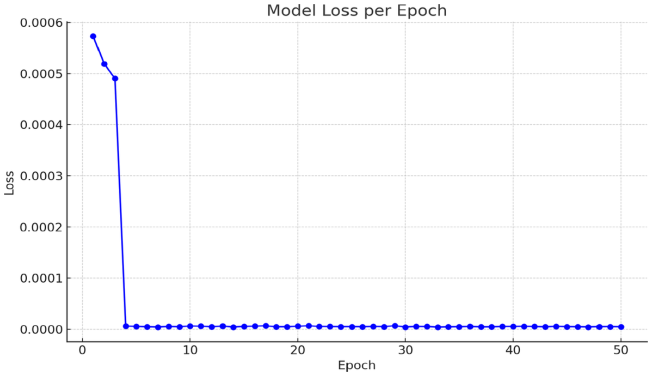

FIGURE 6 | Epoch loss graph of TFT model.

4.2 | Incorporation of Dummy Variables in Modeling

The Bitcoin price is directly affected by major macroeconomic and political developments, in particular regulatory decisions. In this study, to better understand the impact of regulatory changes and global events on the Bitcoin price, dummy variables were also included in the modeling. By incorporating these variables into the TFT model, it was possible to monitor changes in the model's Bitcoin forecasting performance and analyze the

FIGURE 7 | Training and test prediction of the TFT model.

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impact of dummy variables on the Bitcoin price. In this context, the effect of these variables was analyzed quantitatively, both by analyzing trends over time and by comparing price differences between active and inactive periods.

Dummy variables are added to the dataset to represent specific regulatory decisions and significant events that affect the Bitcoin price. Each dummy variable is coded with values of 1 and 0 to capture the impact of a particular event or regulatory decision. One represents the period when the event in question was active, while 0 represents the period when it was inactive. For instance, the variable "China Mining Ban" is coded as 1 from May 3, 2021, when China's Bitcoin mining ban began, and 0 for all periods prior to that date. Similarly, the variable "COVID Impact" is considered active from March 2, 2020, when the global impact of the COVID-19 pandemic began, and is assigned a value of 1 for the period after this date. All dummy variables were added to the dataset by manually determining date ranges according to methods accepted in the literature, in order to accurately represent the event-based

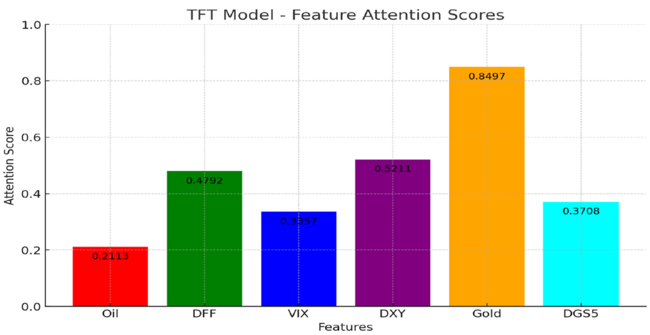

FIGURE 8 | Importance ranking of global variables based on attention mechanism of TFT model.

impacts in the model. This process increased the sensitivity of the model to regulatory decisions and macroeconomic events, allowing a better understanding of how the Bitcoin price is affected by these factors. In this context, the list of dummy variables included in the modeling, their purpose and details are shown in Table 6.

By simultaneously considering both continuous (macroeconomic) and event-based (dummy) variables that affect the Bitcoin price, the goal is to improve the way the Bitcoin price is affected by regulatory decisions and global events, as well as to improve the performance of the model and provide better forecasts. In this way, the Bitcoin price will be predicted more accurately and the dynamics of the market in different time periods will be understood. The training, testing, and cross-validation results of the model with the inclusion of dummy variables are shown in Table 7.

The results in Table 8 show a very high model accuracy with R^2 values of 0.9935, 0.9904 and 0.9934 in the training, test and 5-fold cross-validation sets of the TFT model respectively. When analyzing the error metrics, low error rates are observed in the training set with MAE and RMSE values of 0.0119 and 0.0183 respectively. The MAE, MAPE and RMSE values in the test set are 0.0151, 3.8763 and 0.0238 respectively, and these results show that the model provides consistently high accuracy and low error rates. In addition, 5-fold cross-validation shows that the MAE is 0.0110, the MAPE is 2.7582 and the RMSE is 0.0184. These metrics highlight the consistent performance and generalizability of the model. When comparing the model results in Table 5, where the dummy variables are not included, it is noteworthy that similar results are obtained in the training, test and cross-validation sets. Although there is no significant difference in the performance metrics, the inclusion of dummy variables in the model has led to a better capture of regulatory decisions and

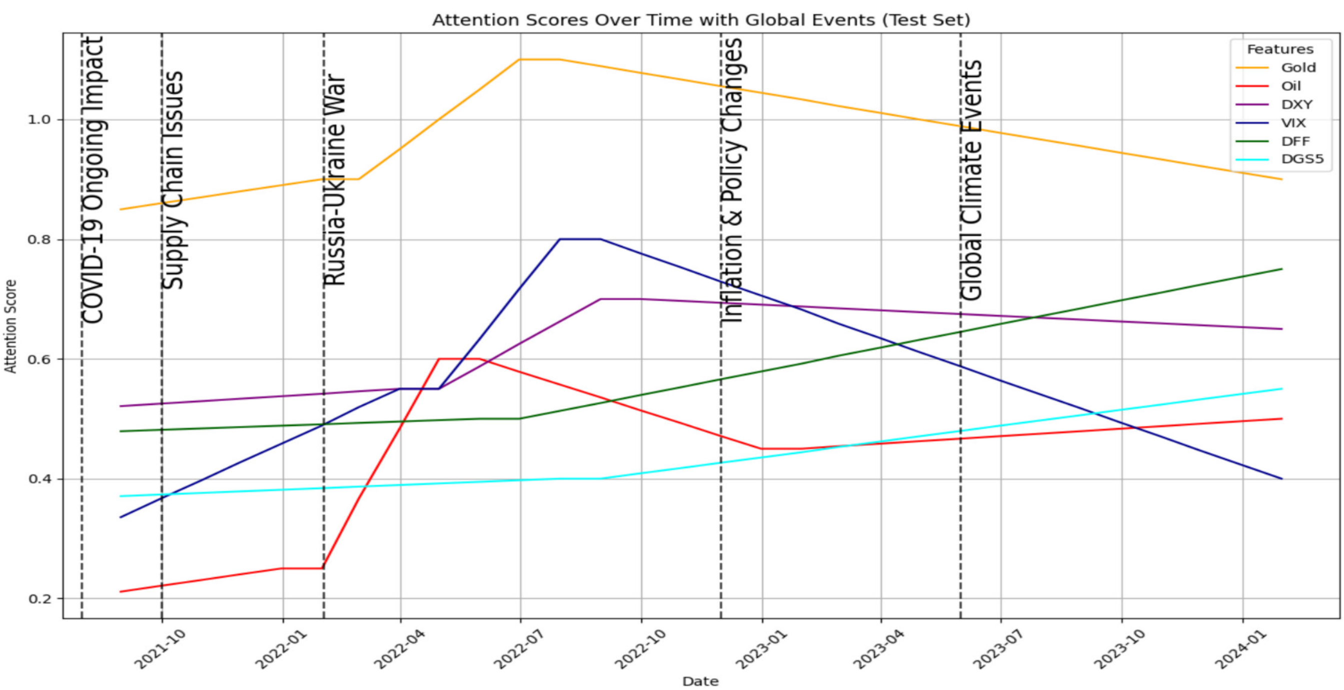

FIGURE 9 | Attention scores over time with global events.

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TABLE 6 | Dummy variables included in the modeling and their details.

Dummy variable	Description	Purpose in the model	Active period	Passive period
COVID impact	The impact of the COVID-19 pandemic on the Bitcoin price.	To evaluate the impact of the pandemic on Bitcoin price trends.	02/03/2020–31/12/2021	03/01/2012–01/03/2020
Global climate events	The impact of global climate-related developments and decisions on the Bitcoin price.	To examine the effects of climate-related regulations on the Bitcoin price.	03/01/2023–08/02/2024	03/01/2012–31/12/2022
China mining ban	The effect of China's Bitcoin mining ban on the Bitcoin price.	To analyze the impact of China's mining ban on Bitcoin price dynamics.	03/05/2021–08/02/2024	03/01/2012–02/05/2021
Russia–Ukraine war	The impact of the Russia–Ukraine war on the Bitcoin price.	To assess the effects of geopolitical developments on the Bitcoin price.	24/02/2022–08/02/2024	03/01/2012–23/02/2022
El Salvador Bitcoin law	The effect of El Salvador adopting Bitcoin as legal tender on the Bitcoin price.	To understand the impact of Bitcoin adoption on its market price.	07/09/2021–08/02/2024	03/01/2012–06/09/2021
Tesla Bitcoin adoption	The impact of Tesla accepting Bitcoin as a payment method on the Bitcoin price.	To evaluate the effects of corporate adoption of Bitcoin on its price.	08/02/2021–12/05/2021	03/01/2012–07/02/2021
Tesla Bitcoin withdrawal	The impact of Tesla ceasing Bitcoin payments due to environmental concerns.	To examine the impact of corporate policy changes on the Bitcoin price.	13/05/2021–08/02/2024	03/01/2012–12/05/2021
Global inflation policy	The impact of global inflation and central bank policies on the Bitcoin price.	To analyze the effects of inflation and monetary policies on the Bitcoin price.	04/01/2021–08/02/2024	03/01/2012–03/01/2020
China exchange restrictions	The effect of China's restrictions on cryptocurrency exchanges on the Bitcoin price.	To assess the impact of regulatory restrictions on cryptocurrency exchanges on the Bitcoin price.	04/01/2021–31/12/2021	03/01/2012–03/01/2021
Supply chain issues	The impact of post-pandemic supply chain issues on the Bitcoin price.	To evaluate the effects of economic uncertainties on the Bitcoin price.	01/06/2021–31/01/2022	03/01/2012–30/05/2021

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TABLE 7 | Training, testing, and cross-validation performance metric results of the model with dummy variables integrated.

Model	Set	R^2	MAE	MAPE	MSE	RMSE
TFT model with integrated dummy variables	Training	0.9935	0.0119	3.2121	0.0003	0.0183
	Test	0.9904	0.0151	3.8763	0.0005	0.0238
	5-fold cross-validation	0.9934	0.0110	2.7582	0.0003	0.0184

TABLE 8 | Unit root test results.

	ADF		PP		Breakpoint ADF	
VIX	−5.7323	0.0000	−6.6919	0.0000	−7.3964	<0.01
Oil	−2.1008	0.2445	−2.2350	0.1939	−4.0807	0.1303
ΔOil	−37.2755	0.0000	−69.8081	0.0001	−67.8005	<0.01
DXY	−1.5088	0.5292	−1.5760	0.4948	−3.3283	0.4875
ΔDXY	−17.1222	0.0000	−55.3231	0.0001	−55.2798	<0.01
Gold	−0.7790	0.8243	−0.7585	0.8299	−3.4148	0.4329
ΔGold	−40.2931	0.0000	−54.8163	0.0001	−54.8563	<0.01
DGS5	−0.7453	0.8333	−0.8854	0.7933	−3.3542	0.4705
ΔDGS5	−39.6775	0.0000	−55.1299	0.0001	−55.7221	<0.01
DFF	1.4929	0.9993	1.6002	0.9995	−4.4136	0.0545
ΔDFF	−18.1035	0.0000	−58.4174	0.0001	−62.9963	<0.01
Bitcoin	−1.3271	0.6190	−0.8181	0.8134	−4.3416	0.0670
ΔBitcoin	−8.8928	0.0000	−56.5479	0.0001	−56.5250	<0.01

Note: Deterministic components are only constant. Appropriate lag length for ADF tests was selected using AIC for a maximum lag of 24 periods. Appropriate Newey–West bandwidth for PP unit root tests is selected using Bartlett kernel. Break type is an innovation outlier. Break selection method is minimized Dickey-Fuller t-statistic. Δ is the first order difference operator.

event-related effects that affect the Bitcoin price. This increases the explanatory power of the model and provides the opportunity to analyze in detail the impact of economic and political events on market dynamics. In particular, the consistency of the cross-validation results indicates that the generalizability of the model is high and that the combination of both macroeconomic and dummy variables provides a significant advantage for future policy evaluations and forecasting studies.

The attention scores for the TFT model's test set visualize how the model allocates attention to the independent variables and which variables it assigns more importance to. This analysis aims to better understand the model's decision-making process and to technically assess the relative importance of variables on the Bitcoin price. Figure 10 clearly illustrates the distribution of attention between macroeconomic variables and dummy variables.

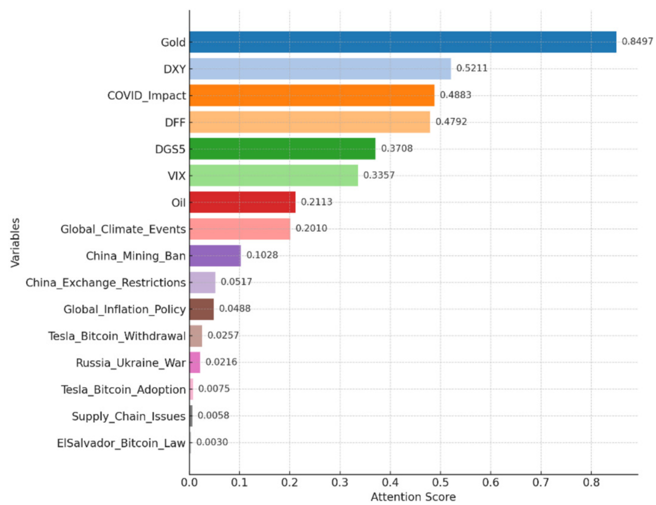

FIGURE 10 | Importance ranking of global variables and dummy variables based on attention mechanism of TFT model.

According to the results, Gold (0.8497), DXY (0.5211) and COVID Impact (0.4883) have the highest attention scores, indicating that these variables are perceived by the model as the most influential factors in predicting the Bitcoin price. Among other macroeconomic variables, DFF (0.4792), DGS5 (0.3708), and VIX (0.3357) also form a significant part of the model. On the other hand, among the dummy variables, Global Climate Events (0.2010) and China Mining Ban (0.1028) have lower attention scores, but play an important role in capturing the impact of regulatory and event-related effects on Bitcoin price fluctuations. These results suggest that the inclusion of dummy

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variables in the model increases the explanatory power of the model by helping to capture regulatory decisions and event-driven effects, and contributes to more accurate predictions. The analysis shows that the model gives more weight to macroeconomic variables, but event-related dummy variables are a complementary element that supports the overall performance of the model. These results prove that the TFT model is a powerful tool for understanding the dynamics of the Bitcoin price.

In Figure 11, the percentage changes in the Bitcoin price are shown separately for the periods when each dummy variable is active. This analysis aims to quantitatively assess the impact of regulatory decisions and global events on the Bitcoin price and to visualize the changes during the periods when each dummy variable is active.

According to the results, the COVID-19 Impact variable generated a striking increase of 419.04% in the Bitcoin price during the period it was active, revealing the intense impact of the pandemic on Bitcoin. Similarly, Global Climate Events stands out with an increase of 172.52%, highlighting the impact of environmental regulations on the Bitcoin market. On the other hand, the China Mining Ban variable had a negative impact on the Bitcoin price with a decrease of 20.52%, indicating the pressure of regulatory restrictions on the market. Among other variables, China Currency Restrictions and Global Inflation Policy had a positive change of 44.33% and 41.90%, respectively, while El Salvador Bitcoin Law and Russia-Ukraine War had limited effects. This analysis provides valuable insight into the importance of regulatory decisions and event-driven effects on Bitcoin price fluctuations. These changes in the active periods of the dummy variables prove that the inclusion of these variables in the modeling process provides a better representation of event-related effects on the Bitcoin price.

Figure 12 visualizes the trend of the Bitcoin price over time and the effects of the periods when the dummy variables with the highest attention scores according to the model were active. The chart highlights periods with significant regulatory and event-based impacts such as COVID Impact, Global Climate Events, and China Mining Ban in different colors. This analysis aims to periodically examine the impact of these events on Bitcoin price dynamics.

According to the results in Figure 12, during the COVID-19 impact period (blue area), the Bitcoin price rose rapidly due to the uncertainties created by the pandemic and global stimulus packages. This period reflects the increasing perception of Bitcoin as a hedging instrument. During the China Mining Ban period (green area), the shock to the supply side of the market caused by China's mining ban led to price volatility and demonstrated that the decentralized nature of Bitcoin was being stress-tested. During the period of global climate events (brown area), increasing criticism of environmental regulations and the carbon emissions of Bitcoin mining showed the market's sensitivity to these issues. The figure also shows that the Bitcoin price was affected by these events to varying degrees and that these effects shaped market dynamics. Economically, these results suggest that regulatory decisions and event-driven shocks affect not only the Bitcoin price, but also market stability and investor behavior. In this context, the high sensitivity of the Bitcoin price to global macroeconomic dynamics and regulatory frameworks provides an important insight into understanding the volatility and speculative nature of financial assets. This analysis can be instructive in determining how market participants should position themselves against regulatory and event-driven risks.

4.3 | Findings From VAR Analysis

The Augmented Dickey–Fuller (1981) and Phillips–Perron (PP, 1988) tests are examples of techniques that are often used in the field of applied research. The purpose of these tests is to examine the null hypothesis, which asserts that the time series has a

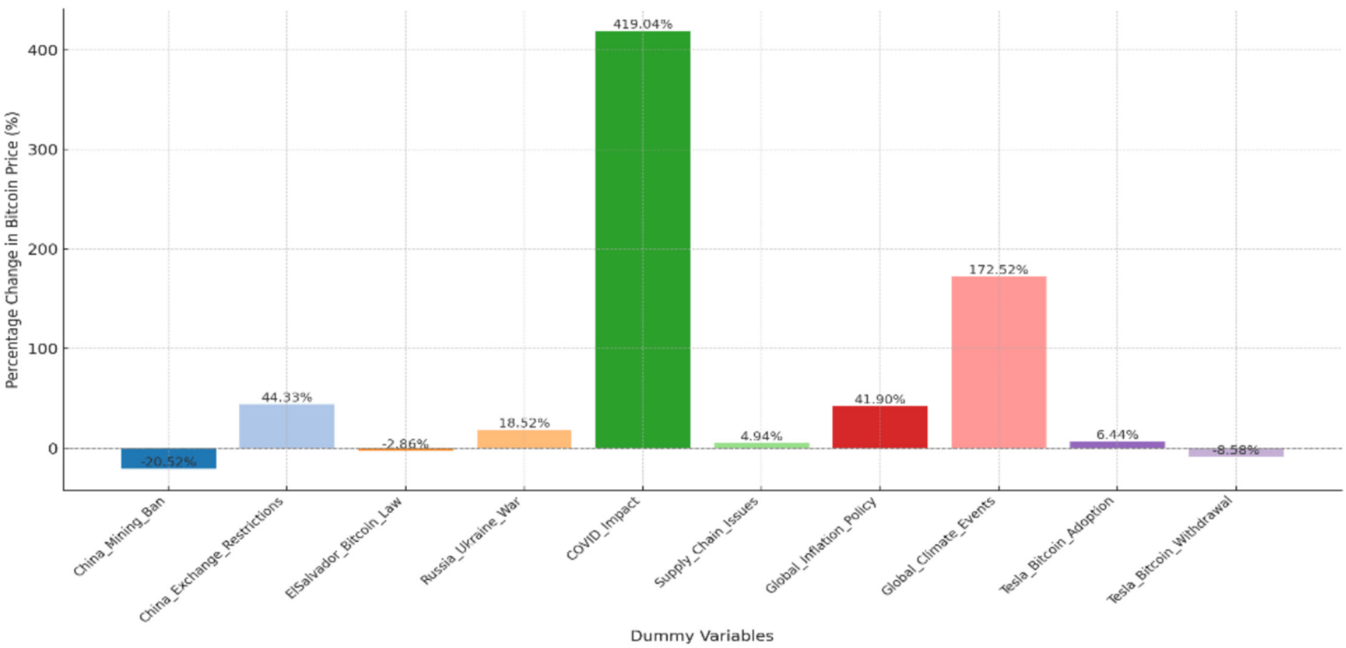

FIGURE 11 | Percentage change in Bitcoin price during active periods.

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FIGURE 12 | Trend analysis of the Bitcoin price with active periods of dummy variables with high attention scores.

unit root, in comparison to the alternative hypothesis, which asserts that the time series does not have a unit root. When a broken trend is present, the ADF test, according to Perron (1989), has a tendency to reject the unit root null hypothesis. This bias happens when the trend is broken. Unit root tests are provided by Zivot and Andrews (1992), Perron (1997), and Vogelsang and Perron (1998). These tests make it easier to identify structural breaks within the data that are endogenous. The ADF, PP, and Vogelsang–Perron (breakpoint ADF) with structural breaks were the three distinct unit root tests that were used in this investigation in order to conduct a reliable evaluation of the stationarity of the variables. Table 8 displays the outcomes of the tests done to determine the unit root. At a significance level of 1%, the results of the findings of the different three-unit root tests indicated consistent outcomes. All variables, with the exception of the VIX, display stationarity at the first-order differences; however, the VIX is the only variable that exhibits stationarity at the level. Despite the fact that the integration order for the VIX is zero, the integration order for the other variables is determined to be one respectively.

In the VAR analysis, the variables are used in their stationary phase. An implementation of the Cholesky decomposition was carried out by taking into account the ordering of the variables as follows:VIX, DGS5, DFF, DXY, Gold, Oil, and Bitcoin. The appropriate lag length for the VAR model was determined to be 27 using AIC, while the maximum lag was 48.

Figure 13 illustrates the Bitcoin price's response to the chosen factors. The Bitcoin price had a significant negative response to the VIX throughout the first two periods. When it came to the response of the Bitcoin price to DFF, the same impact was identified, and the response was statistically significant and negative in the first three periods. The Bitcoin price had a positive and statistically significant response to DGS5 in the first period. The Bitcoin price did not exhibit a statistically significant response to DXY. In the initial periods, the Bitcoin price did not exhibit a significant response, as indicated by the findings regarding the gold and oil prices. The response to the gold price became statistically significant and negative in the fifth period. Despite the brief span of the impact, the response became negative and reached statistical significance in the sixteenth period. This indicates that the gold price has a substantial impact over the long term. The evaluation of the oil price yielded a negative and statistically significant response in the sixth period. The Bitcoin price exhibited a positive and statistically significant reaction to its own fluctuations in the first periods. The importance of the response was evident in the fourth, eighth, 13th, 16th, 20th, and 23rd periods. The result suggests that the Bitcoin price was mostly affected by its own price fluctuations. These findings suggest that Bitcoin is a speculative asset, mostly driven by its own price fluctuations.

5 | Discussion

The findings of this study provide important insights into the dynamic and multifaceted relationships between the Bitcoin price and global economic variables. This section aims to contextualize the results within the broader academic and practical landscape by addressing implications for policymakers, investors, and academics. The TFT model emerged as the most successful forecasting approach among the models tested, showing superior accuracy across all performance measures. The ability of this model to capture both short-term and long-term dependencies in time series data underlines its suitability for analyzing volatile and complex markets such as cryptocurrencies. The dominance of the gold price as the most influential variable in

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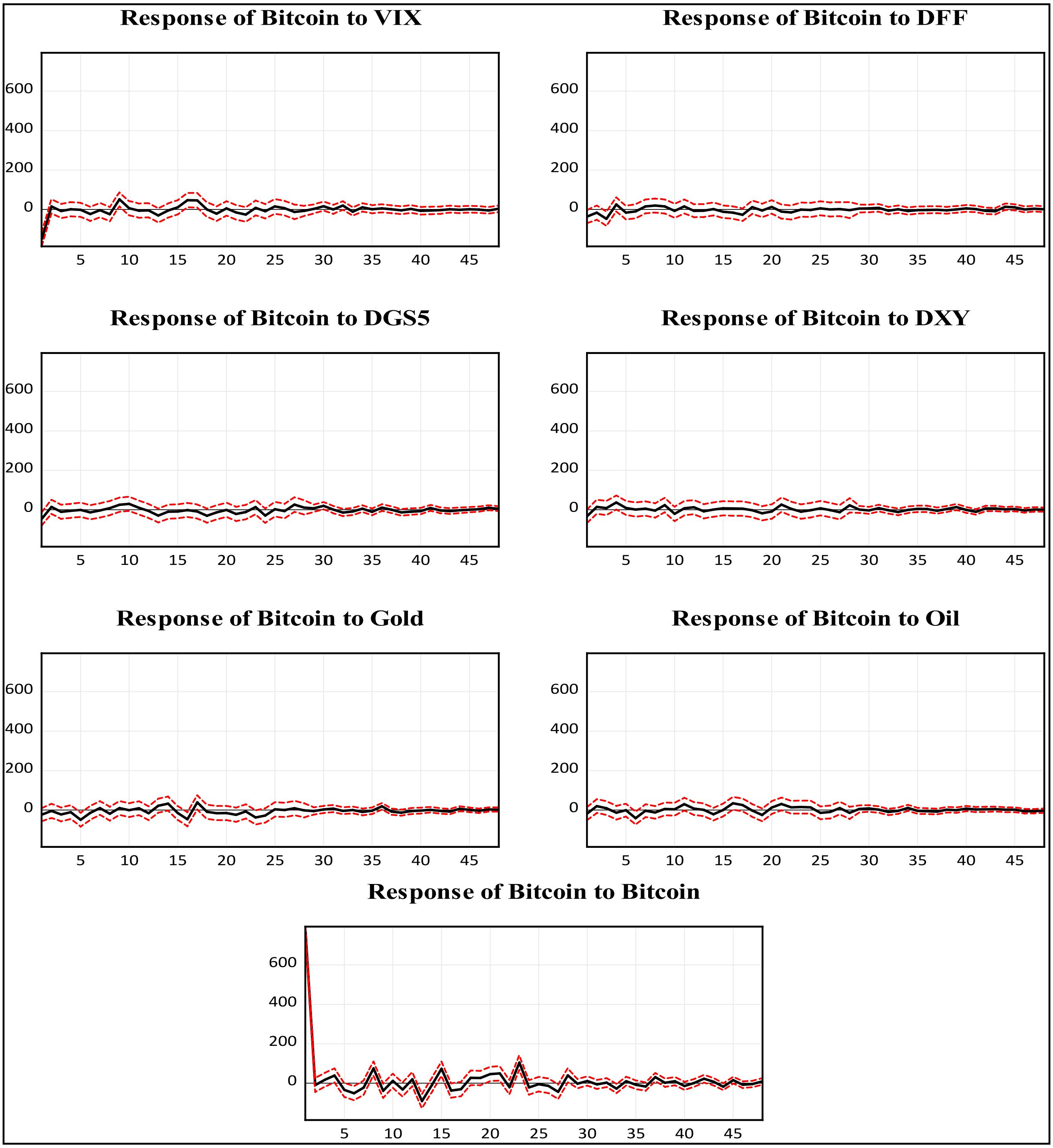

FIGURE 13 | Response of the in ation to structural one standard deviation positive innovations.

Bitcoin price forecasting suggests that Bitcoin continues to be perceived as "digital gold," a safe-haven asset during periods of economic uncertainty. This finding is in line with previous studies that emphasize the substitution relationship between Bitcoin and gold during market turbulence. The negative impact of the oil price on Bitcoin, especially in the long run, reveals an interesting dynamic. This suggests that fluctuations in the global energy market indirectly affect cryptocurrency valuations, possibly through macroeconomic channels such as inflation expectations and investor sentiment. Similarly, the DXY and economic policies (captured by DGS5 and DFF) significantly influence the Bitcoin price, highlighting the role of macroeconomic stability and monetary policy in shaping cryptocurrency markets.

The findings highlight the need for comprehensive regulatory frameworks that recognize the interconnectedness of cryptocurrencies with traditional financial markets. Clear and consistent policies can reduce market uncertainty and promote a stable investment environment. Monitoring macroeconomic indicators such as the gold price and interest rates can provide

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early warning signals for potential fluctuations in cryptocurrency markets, allowing for proactive policy interventions. The findings of the study emphasize the importance of incorporating global economic indicators into investment strategies. Given the sensitivity of the Bitcoin price to variables such as gold and oil, diversified portfolios that take these relationships into account can reduce risks and increase returns.

The results of this study are largely in line with previous studies in the literature, but some differences were also observed. For instance, studies in the literature using traditional methods such as ARIMA, GARCH, and Bayesian models in Bitcoin price forecasting (Huang et al. 2022; Aysan et al. 2019) emphasized that these models may be inadequate for nonlinear and highly volatile financial data. Similarly, studies such as Ngai et al. (2023) and Mahfooz and Phillips (2024) have shown that DL models such as LSTM and GRU have superior performance on time series data. In this study, LSTM, GRU, and especially TFT models provide high accuracy rates in predicting the Bitcoin price, supporting the success of DL models in nonlinear data structures. Moreover, the performance limitations of ML models highlighted by Siva, Subrahmanian, and Chaturya (2024) were also observed in this study, with LightGBM and XGBoost models exhibiting lower performance compared to DL models, especially in the testing and cross-validation phases. In conclusion, this study largely agrees with the findings in the literature and once again shows that DL models are more effective in predicting volatile assets such as Bitcoin. However, the results of this study reveal the superior performance of DL models when compared to the metric results obtained in similar studies in the literature. For example, in Ngai et al. (2023), the R^2 score of the LSTM model was reported as 0.87, while in this study, the LSTM model achieved an R^2 value of 0.9857 in the training set and 0.9854 in the test set. Similarly, Mahfooz and Phillips (2024) obtained a MAPE of 2.1% for the LSTM model, whereas in this study, the MAPE of the LSTM in the test set was 4.77%, which may reflect the more complex nature of the dataset and the longer time interval. While the CNN model is also notable for its lower error rates in the literature (Dutta, Kumar, and Basu 2020), in this study, it yielded successful results such as 0.9882 R^2 and 3.42% MAPE on the training set. Looking at ML models, Siva, Subrahmanian, and Chaturya (2024) stated that the XGBoost model underperformed with a MAPE of 7.76%, while in this study, the MAPE value of XGBoost in the test set was measured as 20.21%, which shows that it has a lower performance compared to DL models. While the LightGBM model is found to be successful in the literature with a MAPE of 4.44% (Zuo 2024), in this study, a similar MAPE of 4.44% was obtained in the training set, but a slightly higher error rate of 5.39% was observed in the test set. These comparisons show that the DL models used in this study are in line with and generally outperform other studies in the literature, while the ML models perform similarly to the results in the literature.

VAR analysis showed that the Bitcoin price is often influenced by its own past values and fluctuations. This result is in line with the existing literature that Bitcoin is a speculative asset (Su et al. 2022; Mnif, Mouakhar, and Jarboui 2022). The fact that the Bitcoin price is driven by its own dynamics emphasizes the importance of market sentiment on this asset. In particular, Bitcoin-specific sentiment factors appear to be a critical factor affecting investors' decisions. These findings confirm the importance of Bitcoin-specific sentiment measures (e.g., TRMI) emphasized by Aysan et al. (2023). Moreover, the VAR analysis results reveal that the relationship between Bitcoin and other macroeconomic indicators is cyclical and shows a lower dependence in the long run. This reflects the speculative nature of Bitcoin, which changes according to market conditions.

The sliding window correlation analysis used in this study has shown that the relationship between Bitcoin and gold is not static, but changes periodically. For instance, the safe-haven behavior proposed by Dyhrberg (2016) was confirmed during certain periods of economic uncertainty, while the weak relationship highlighted by Siauwijaya and Sanjung (2022) emerged during more speculative market conditions. The results of the analysis clearly reveal that the Bitcoin-gold correlation varies depending on macroeconomic and market conditions. The sliding window correlation analysis revealed that the relationship between Bitcoin and gold prices changes dynamically over time. These findings are consistent with the financial asset substitution theory. Financial asset substitution theory suggests that investors can reduce their risk exposure by reallocating their investments between different asset classes, especially during periods of economic uncertainty or inflation. This strategy is based on the understanding that various assets respond differently to economic conditions and allows investors to optimize their portfolios by substituting one asset for another according to current market dynamics (Sharma et al. 2006; Brogaard and Detzel 2015). The results of the analysis indicate that Bitcoin is highly correlated with gold in certain periods, which may indicate that investors prefer Bitcoin as an alternative safe haven. However, the fact that the correlation turns negative during periods of divergence suggests that Bitcoin functions as a speculative instrument rather than moving together with traditional assets. For instance, the short-term fluctuations seen in the 30-day window analyses showed that the volatility of the Bitcoin market was much higher compared to gold. On the other hand, the 90-day window analyses revealed that in longer-term trends, Bitcoin is occasionally correlated with gold, but this relationship is strongly influenced by economic, political and market dynamics. This dynamic relationship suggests that while Bitcoin has traditional safe-haven characteristics, it is a more speculative and market-sensitive asset. Especially in the 2016–2020 period, economic uncertainties and regulatory changes strengthened the positive correlation between Bitcoin and gold. Nevertheless, the market after 2021 and the increased interest of institutional investors in Bitcoin weakened this relationship and led to Bitcoin's positioning as an independent investment instrument.

6 | Conclusion

This paper presents a comparative analysis of DL and ML techniques to predict the Bitcoin price over the period 2012–2024. The models used include LSTM, GRU, CNN, TFT, XGBoost, LightGBM, and SVR. The findings of the study show that DL models perform better than ML models, especially on volatile financial data such as Bitcoin. In particular, TFT and CNN models stood out with high accuracy rates in the test set. The TFT model showed the highest performance by successfully modeling complex relationships and non-linear structures in

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time series. Among the ML models, LightGBM generally performed better than the other models; however, it was observed that its performance lagged behind when compared to DL models. These findings suggest that DL models have superior performance, especially in time series forecasting, and are an effective method for price prediction of volatile assets such as Bitcoin. The results obtained in the study show that DL models can be successful, especially in complex financial data.

When the attention score results obtained from the attention mechanism of the TFT model are analyzed, the highest score is given to the Gold variable with 0.8497, and it is observed that this variable is the most important factor in predicting the Bitcoin price. Gold has historically been seen as a safe haven and is in high demand during periods of inflation and economic uncertainty, which increases its impact on the Bitcoin price. The DXY came in second at 0.5211, having a large impact on the Bitcoin price due to the critical role the US dollar plays during global economic uncertainties. More stable global indicators such as the DFF and DGS5 also received high attention scores and were particularly prominent during inflationary periods. Variables such as the VIX and Oil, on the other hand, showed cyclical effects and were important in the short run, especially during global events, but received lower attention scores overall. These findings are also supported by the results of the VAR analysis. According to the VAR analysis, shocks to the VIX and DXY led to short-term fluctuations in the Bitcoin price, and especially the effect of DXY on Bitcoin was found to be significant. On the other hand, variables such as Gold and DFF had significant effects on the Bitcoin price both in the short and long run. In particular, the effect of gold on the Bitcoin price is in line with the attention scores of the TFT model, while the role of DFF and DGS5 in economic policies and economic expectations is also emphasized in both VAR analysis and TFT attention scores. Oil and VIX, on the other hand, showed a larger impact during cyclical events but had a more limited role in the overall analysis. These results support the sensitivity of the Bitcoin price to global indicators and how the effects of these indicators change over time through both the attention mechanism and VAR analysis.

DL models are more successful thanks to their capacity to learn non-linear relationships, especially in time series. The TFT model showed the highest performance in the test set with results such as 0.9904 R^2 and 0.0151 MAE. The CNN model also showed strong results, while the ML model LightGBM showed the best results, but its performance lagged behind compared to DL models.

Significant differences were observed between the performance of the models. TFT stood out with the lowest MAE (0.0151) and MAPE (3.87%). CNN followed with an R^2 of 0.9872 and a MAPE of 4.23%, while the LSTM and GRU models also performed strongly. On the ML side, LightGBM gave the best results with an R^2 of 0.9897 and a MAPE of 5.39%, while XGBoost and SVR underperformed, especially SVR's MAPE of 21.99% was significantly higher than the other models.

According to the results obtained from the attention mechanism of the TFT model, gold had the largest impact on the Bitcoin price during periods of inflation and uncertainty. The DXY and VIX, on the other hand, caused significant short-term fluctuations in the Bitcoin price, especially during events such as the COVID-19 pandemic and the Russia-Ukraine war. The VAR analysis also supported these findings, showing that the DXY had a significant impact on the Bitcoin price in the short term. DFF and DGS5, on the other hand, played a more significant role in relation to inflationary pressures and interest rate policies affecting the Bitcoin price in the short to medium term.

The findings of this study highlight the impact of global indicators, especially gold and DXY, on the Bitcoin price. Investors are advised to closely monitor these factors to anticipate Bitcoin price movements during global economic uncertainties, inflationary periods, and central bank policies. In particular, gold's role as a safe haven may influence Bitcoin demand during periods of inflation and economic uncertainty, suggesting a correlation between gold and Bitcoin during these periods. Similarly, the role of the DXY on global economic stability may have an impact on the demand for Bitcoin as an alternative asset. Bitcoin's strong correlation with the DXY questions the argument that Bitcoin can be an alternative currency outside the control of governments. The influence of the DXY shows that Bitcoin is sensitive to global economic conditions and the US dollar. This may limit Bitcoin's positioning as a fully independent asset. Furthermore, Bitcoin's high volatility and dependence on market sentiment also limits its capacity as a safe haven. However, the speculative nature of Bitcoin complicates its role as an alternative currency or store of value. For Bitcoin to fulfill these roles, it needs to develop regulations to reduce market volatility and a less dependent relationship with the global economic system. For policymakers, the study finds that interest rate variables such as the DFF and DGS5 have significant effects on the Bitcoin price. This may suggest that policymakers and stakeholders should consider the impact of interest rate policies on speculative assets and take into account the market movements of such assets when creating policy. Moreover, since market uncertainties and inflationary pressures may cause volatility in the Bitcoin price, it should be taken into account that Bitcoin and other digital assets may affect investor behavior when formulating policies.

In addition, the regulatory decisions and global events were incorporated into the TFT model. The impact of the COVID-19 pandemic played a considerable role in explaining the Bitcoin price. Subsequently, both global climate events and China's mining ban significantly impacted the Bitcoin price. The findings suggest that, in along with macroeconomic factors, regulatory actions and global events strongly influence the Bitcoin price.

The predictive success of advanced models such as TFT suggests that integrating state-of-the-art ML tools into investment decision-making can provide a competitive advantage in volatile markets. In the context of academic research, this study extends the existing methodological toolkit for cryptocurrency analysis by demonstrating the effectiveness of TFT and other advanced models. Future research can build on this foundation to explore additional variables and alternative modeling techniques. The analysis of the fluctuating correlation between Bitcoin and gold highlights the dynamic nature of their relationship. Further exploration of the reasons for these fluctuations, such as geopolitical events or changes in investor behavior, could provide deeper insights. The dataset used in this study covers the period 2012–2024,

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during which major global events such as the COVID-19 pandemic and the Russia-Ukraine war took place. The effects of such events on the Bitcoin price have been analyzed, but it is not possible to isolate exactly how they affect the overall model performance. Furthermore, only certain global variables (Gold, DXY, VIX, DFF, DGS5, and Oil) were used, and no other important financial indicators were included in this study. Factors that may have an impact on the Bitcoin price, such as regulations, developments in cryptocurrency exchanges, and technological innovations, are excluded from the analysis. Finally, this study focuses only on DL and ML models, and other alternative modeling and optimization techniques could not be evaluated. Future studies can examine the Bitcoin price from a broader perspective by considering more global and financial variables. In particular, the impact of cryptocurrency regulations, central banks' digital currency policies, and developments in blockchain technology on the Bitcoin price should be investigated. Longer-term analysis and examining the effects on the Bitcoin price in different geographical regions may provide more comprehensive insights into investor behavior. Moreover, testing alternative modeling methods (e.g., hybrid models and reinforcement learning) and more advanced optimization techniques (e.g., Bayesian optimization) may be useful to improve model performance and achieve more reliable results in price forecasts of volatile assets such as Bitcoin. Finally, investigating other influences on Bitcoin, such as non-time-series events (e.g., large stock market movements and political developments), could provide further insights in predicting Bitcoin price movements.

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Conflicts of Interest

The authors declare no conflicts of interest.

Data Availability Statement

Various sources were used to collect data for the analyses. Each source of data and materials has been available and pointed through the paper.

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