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SURVEY

From Prediction to Profit: A Comprehensive Review of Cryptocurrency Trading Strategies and Price Forecasting Techniques

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ABSTRACT The rapid evolution of cryptocurrency markets and the increasing complexity of trading strategies necessitate a comprehensive understanding of price-prediction models and their direct impact on trading efficacy. While extensive research has been conducted separately on price prediction methods and trading strategies, there remains a significant gap in studies explicitly correlating precise price forecasts with successful trading outcomes. This review paper addresses this gap by critically examining the role of accurate cryptocurrency price predictions in enhancing trading strategies. We conducted a systematic review of sufficient scholarly articles and web resources, focusing on the methodologies and effectiveness of various predictive models and their integration into cryptocurrency trading strategies. Our selection criteria ensured the inclusion of papers that demonstrate methodological rigor, relevance, and recent contributions to the field, spanning from economic theories and statistical models to advanced machine learning techniques. The findings reveal that precise price predictions significantly contribute to the development of adaptive and risk-managed trading strategies, which are crucial in the highly volatile cryptocurrency market. The review also identifies current challenges and proposes directions for future research, emphasizing the need for interdisciplinary approaches and ethical considerations in predictive modeling. This synthesis aims to bridge the existing research gap and guide future studies, thereby fostering more sophisticated and profitable trading strategies in the cryptocurrency domain.

INDEX TERMS Cryptocurrency trading, price prediction, trading strategies, machine learning.

I. INTRODUCTION

The burgeoning field of cryptocurrency trading has captured the interest of investors and researchers alike, due to its pronounced volatility and potential for high returns. Efficient trading within these digital asset markets relies heavily on the ability to forecast price movements accurately. As a result, the development and refinement of price-prediction models have become crucial for traders aiming to maximize returns and minimize risks. The significance of price predictions in cryptocurrency trading cannot be overstated, as these predictions serve as a foundation for constructing robust trading strategies. Kristoufek [1] highlights the multifaceted influences on Bitcoin prices, including both market demand and technological changes. Furthermore, machine learning models, such as those investigated by Alessandretti et al. [2], demonstrate the effectiveness of complex algorithms like neural networks in predicting cryptocurrency prices with a notable degree of accuracy.

Incorporating sentiment analysis and macroeconomic indicators further enhances our understanding of external impacts on price volatility. Studies such as those by Shah and Zhang [3] and Corbet et al. [4] delve into these aspects, with focusing on Bayesian regression methods for

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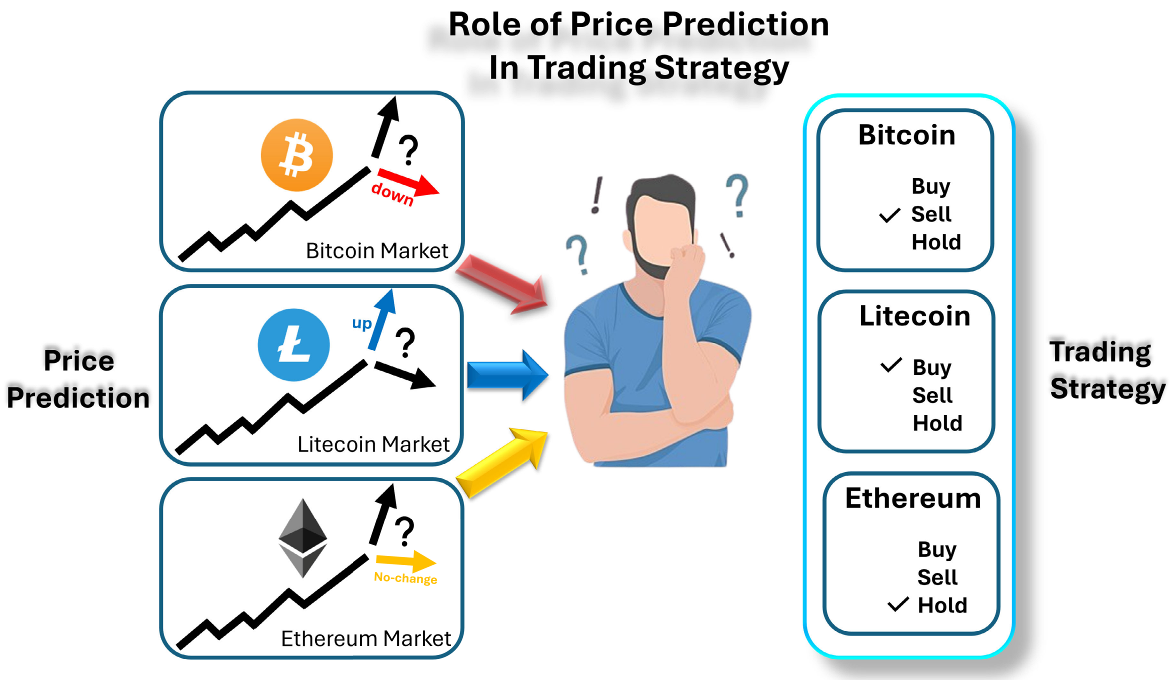

FIGURE 1. Motivation for defining the role of price prediction in trading strategy.

Bitcoin price prediction. Similarly, Georgoula et al. [5] uses Google Trends data to examine the link between search queries and Bitcoin prices, showing how investor interest can serve as a predictive indicator. The impact of global economic events on cryptocurrencies, as studied by Fry and Cheah [6], and the application of hybrid models that combine various predictive techniques like those by Garcìa-Medina and Aguayo-Moreno [7], further demonstrate the breadth of research in this area. These predictive models not only facilitate more informed trading decisions but also contribute to the broader financial landscape by offering stability and predictability in otherwise turbulent markets. Combining these varied approaches—ranging from econometric models to data-driven algorithms—yields a comprehensive toolkit for traders. This integration is pivotal in developing advanced trading strategies that adapt dynamically to the ever-changing cryptocurrency market. This convergence of predictive accuracy and strategic application underscores a vital area of research that promises to refine and revolutionize the approaches used in cryptocurrency trading, guiding us toward a more systematic understanding of the interplay between prediction models and trading efficacy.

Numerous survey papers have addressed different aspects of cryptocurrency trading, yet they typically narrow their focus. Sharma et al. [8] offered an initial overview of cryptocurrencies, noting their benefits over traditional fiat currencies and comparing various cryptocurrency systems. Following this, Mukhopadhyay et al. [9] provided an analysis of cryptocurrency systems. Kyriazis [10] explored the market's efficiency and potential for profitable trading opportunities, pinpointing crucial strategies for traders. Moreover, Merediz-Solà and Bariviera [11] executed a bibliometric study that was exclusively centered on Bitcoin literature. These studies, while informative, tend to concentrate on introductory aspects of cryptocurrencies, specific platforms, or the bitcoin market itself, rather than a holistic view of trading strategies enhanced by accurate price predictions. To the best of our knowledge, no previous work has provided a comprehensive survey specifically focused on how various predictive models enhance cryptocurrency trading strategies. This gap highlights the unique contribution of our review, which aims to integrate these disparate studies and provide a unified framework that examines the practical applications of predictive accuracy in trading strategies within the dynamic cryptocurrency markets. Figure 1 visually represents the conceptual framework of this survey, highlighting how accurate price predictions are reliable in trading strategies. In pursuit of this understanding, our review aims to explore the role of accurate price predictions in shaping effective trading strategies within the cryptocurrency market.

In our survey, we concentrate primarily on three predominant cryptocurrencies to narrow our focus, as the vast number of available cryptocoins would make a broader study unmanageable:

- Bitcoin (BTC): As the first and most well-known cryptocurrency, Bitcoin offers the longest historical price data, making it a primary focus for predictive analysis and trading strategy development [12].
- Litecoin (LTC): Often considered the silver to Bitcoin's gold, Litecoin provides a different market structure and volatility pattern, useful for comparative analysis [13].

- Ethereum (ETH): With its unique feature of smart contracts and a strong foundation in blockchain applications beyond mere currency, Ethereum offers a broader context for price prediction and its effects on trading strategies [14].

These currencies are chosen for their market maturity, volume, and the extensive range of data available, which makes them ideal subjects for assessing the impact of prediction models on trading strategies. We will cover a variety of trading strategies that are commonly employed in the cryptocurrency markets, focusing on:

- Technical Indicators: These include tools like moving averages, Relative Strength Index (RSI), and MACD (Moving Average Convergence Divergence), which are used to predict price movement based on historical data.
- Algorithmic Trading: This involves the use of automated systems that execute trades based on pre-set criteria derived from predictive models. The review will explore how algorithmic strategies are designed, optimized, and the risks involved.

While this survey comprehensively covers prediction models and trading strategies, it will not delve into the regulatory aspects of the socio-economic implications of cryptocurrency trading. The focus remains strictly on the technical and performance aspects of trading strategies enhanced by predictive models. By setting these parameters, the review aims to provide a focused analysis of how predictive accuracy can be leveraged to optimize trading strategies within the cryptocurrency markets of BTC, LTC, and ETH. This scope ensures that our findings are relevant to traders, investors, and researchers who are engaged with these leading cryptocurrencies.

We summarize our main contributions in more detail as follows:

- **Exploration of Prediction Models**: We provide a comprehensive examination of the diverse prediction models employed in cryptocurrency markets, ranging from econometric models and traditional statistical forecasting to advanced machine learning algorithms. This exploration will assess the theoretical foundations, practical implementations, and performance outcomes of these models in various market conditions.
- **Impact on Trading Strategies:** We investigate how effectively different existing models are integrated into trading strategies and the resultant impact on trading performance. We also analyze the successful applications that have enhanced trading outcomes by classifying them into different classes based on employed algorithms. This review will assess to have a clear image of state-of-the-art trading strategies in the case of three common cryptocoins.
- **Defining the Role of Accurate Prediction:** We delineate the conditions under which accurate predictions can positively influence trading strategies and identify situations where they might not. It will explore the complexities of prediction in volatile markets, including potential pitfalls like overfitting, the influence of market sentiment, and the challenges of adapting to unexpected market events. This includes a critical assessment of cases where predictions may inadvertently increase trading risks or lead to financial losses.
- **Challanges and Future Directions:** We identify current challenges and propose directions for future research, highlighting the need for interdisciplinary approaches and ethical considerations in predictive modeling. This synthesis aims to bridge the existing research gap and guide future studies, thereby fostering more refined and effective trading strategies in the cryptocurrency domain.

By considering these contributions, we aim to shed light on the nuanced relationships between predictive accuracy and trading strategy effectiveness. This insight is crucial for developing more resilient and adaptive trading approaches in the ever-evolving cryptocurrency landscape. Building on the objectives outlined, this review will specifically delineate its boundaries to provide clarity and focus.

The remainder of this paper is methodically arranged to provide an overview and classification of existing studies in Section II, where we outline our literature selection criteria and search strategy. This section seamlessly transitions into an exploration of the fundamental concepts of cryptocurrency trading and price prediction, encapsulating key terminologies and the unique challenges posed by market volatility. In Section III, we categorize and analyze a variety of predictive models used in the field, including economic theories, statistical methods, machine learning techniques, and the role of sentiment analysis. Section IV transitions to how different approaches have been applied in the development of trading strategies, emphasizing the use of technical analysis and algorithmic trading. Section V focuses on the strategic importance of accurate price predictions, assessing how they enhance trading efficiency and adaptability based on reviewed studies. In addition to their importance, it also mentions the challenges and limitations of trading strategies. Forward-looking considerations, including the impact of emerging technologies and regulatory changes on trading strategies, are explored in Section VI. Finally, Section VII concludes the major points and findings from the classified literature, discusses their practical implications for traders and investors outlining the potential directions for future research. Figure 2 is given to visually illustrate the paper structure.

II. METHODOLOGY AND FOUNDATIONS

This section explains our systematic approach to selecting and reviewing literature and showcases the foundational concepts underlying cryptocurrency trading and price prediction. Our discussion begins by detailing the criteria and strategic search methods employed to gather the most relevant and impactful studies. Following this, we delve into the basics of cryptocurrency trading, highlighting key terminologies and the operational mechanisms that define this digital financial

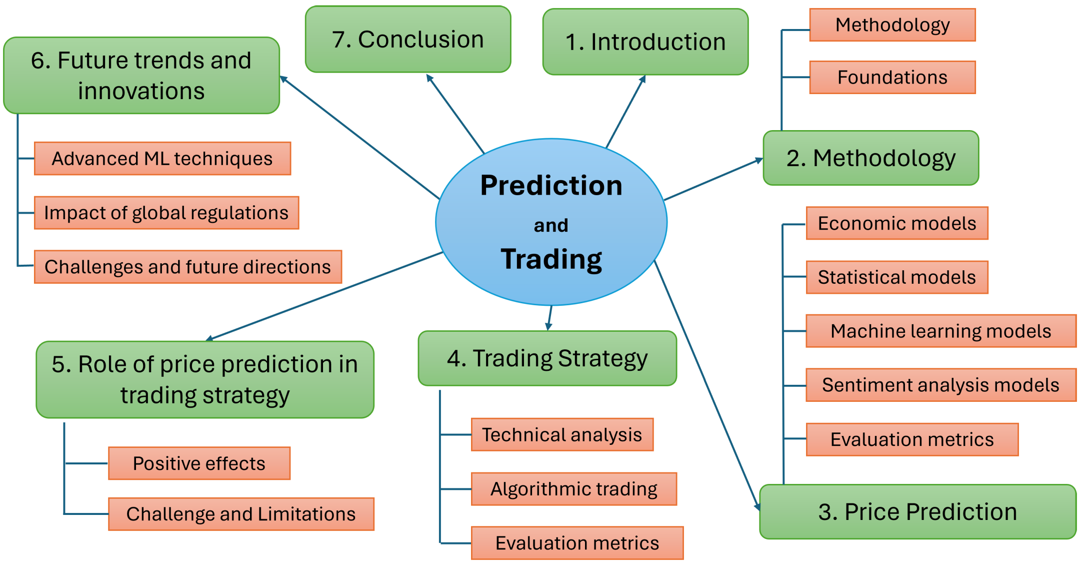

FIGURE 2. Structure of the contents in this paper.

landscape. We then explore the concept of price prediction within these markets, addressing the unique challenges posed by their inherent volatility and the evolving technological landscape that influences them.

A. METHODOLOGY

In our systematic review, the selection of relevant papers and studies is guided by a set of criteria designed to ensure both relevance and rigorous academic standards. These criteria serve as the foundation for the comprehensive analysis of cryptocurrency price prediction and trading strategies.

- **Relevance:** Our primary focus is on studies directly related to cryptocurrency price prediction, trading strategies, or both. This ensures that the selected literature is highly pertinent to our review's objectives, providing insights specifically tailored to understanding the dynamics and mechanisms of cryptocurrency markets.
- **Methodological Rigor:** It is crucial that the studies included in our review adhere to high methodological standards. We prioritize research that utilizes reliable data sources and offers clear, detailed methodologies for data collection, cleaning, and preprocessing. These practices are indicative of the quality and dependability of the research findings, ensuring that our review is based on trustworthy and verifiable information.
- **Impact and Citation:** The influence of a study within the academic community is another important criterion. We consider the citation count as a proxy for a study's impact and acceptance. Studies that are frequently cited by other researchers typically signify a higher relevance and quality. Additionally, research published in reputable journals or presented at prestigious conferences is preferred, as these platforms often involve rigorous peer review processes, further validating the reliability of the findings.
- **Recency:** While the focus is on studies published within the last five years to ensure timeliness and relevance, we make exceptions for seminal works that underpin essential economic theories, trading rules, and technical indicators. These foundational studies often predate the last five years but are crucial for a thorough understanding of the theoretical and practical aspects of trading strategies and their historical development.

These defined criteria along with streamlining the process of selecting the most relevant and authoritative papers, also ensure that our analysis remains focused and applicable to the current state of cryptocurrency trading strategies. Moving forward, to ensure a thorough and comprehensive review of the literature on cryptocurrency price prediction and trading strategies, particularly concerning BTC, ETH, and LTC, we have developed a detailed search strategy. This strategy is designed to capture the most relevant and recent studies, while also including seminal works that provide foundational knowledge.

- **Databases and Search Engines:** Our primary sources for research papers include academic databases such as JSTOR [15], ScienceDirect [16], IEEE Xplore [17], and the ACM Digital Library [18]. These platforms are renowned for their extensive collections of finance and technology-related research. Additionally, for broader searches, we utilize Google Scholar [19] to capture articles and white papers that might not be indexed in the more traditional academic databases.
- **Keywords and Phrases:** The keywords used in our searches are chosen to reflect the focus on our selected cryptocurrencies and the aspects of trading and prediction. The primary keywords include: *"Bitcoin", "BTC", "Ethereum", "ETH", "Litecoin", "LTC", "cryptocurrency price prediction", "cryptocurrency trading strategies", "technical analysis", "algorithmic trading in cryptocurrencies", "machine*

learning in cryptocurrency trading", "economic models in cryptocurrency", "statistical methods for cryptocurrency". These keywords are often combined with additional terms such as *"price volatility", "market dynamics", "predictive accuracy",* and *"trading efficiency"* to refine the searches and ensure comprehensive coverage of the topic.

- **Filtering and Selection Process:** After compiling an initial list of papers, we apply our selection criteria to filter out studies that do not meet our methodological rigor or relevance requirements. This includes reviewing abstracts and methodologies to ascertain the focus and depth of each study, ensuring they align with our review's themes. Papers older than five years are carefully considered for their foundational value before inclusion, especially those that detail economic laws or technical indicators crucial to understanding current practices.

By implementing this search strategy, we ensure that our review is underpinned by the most authoritative and relevant research, providing a solid foundation for analyzing the impacts of price prediction on cryptocurrency trading strategies.

B. FOUNDATIONS

Understanding the foundation terms and mechanisms is crucial for anyone engaging in or studying cryptocurrency price prediction and trading strategy, as they form the basis of more complex discussions. Therefore, we present Table 1, describing an explanation of some of the most famous terms within the cryptocurrency price prediction environment, followed by an explanation of the terms for trading strategies:

Having established the foundational concepts and key terms within the cryptocurrency price prediction and trading landscape, we now shift our focus to reviewing recent research studying price prediction tasks in this survey.

III. CRYPTOCURRENCY PRICE PREDICTION

Predicting the price movements of cryptocurrencies is an intricate endeavor that blends finance, economics, and computer science into a singular pursuit aimed at deciphering one of the most volatile segments of the market. As cryptocurrencies continue to forge a significant path through global finance, understanding the diverse methodologies employed to predict their prices is crucial for both academics and practitioners. This section explores the range of models used to forecast cryptocurrency prices, each offering distinct perspectives and tools. Figure 3 illustrates the diverse range of utilized in cryptocurrency price prediction tasks.

A. ECONOMIC MODELS

Cryptocurrency markets, exemplified by BTC, ETH, and LTC, operate under unique market dynamics and face significant price volatility, posing challenges and opportunities in economic modeling and prediction. In recent years, several studies have observed the influence of macroeconomic indicators on the cryptocurrency price. For example, Dutta et al. [38] and Wang and Vergne [39] examined how macroeconomic indicators such as interest rates, S&P500 returns, US bond yields, and the overall gold price level impact Bitcoin prices. They discovered that while these factors possess short-term predictive power for Bitcoin returns, the supply of Bitcoin in circulation also shows a strong positive correlation with its weekly returns. Kristoufek [1] extended this research, finding that Bitcoin's long-term appreciation is linked to its increased use in non-exchange transactions. Along with these indicating factors, the fundamental economic principles of supply and demand are important in understanding cryptocurrency valuation. Conrad et al. [40] highlighted how S&P500 volatility positively affects long-term BTC volatility, underscoring the complex interaction between macroeconomic stability and cryptocurrency prices. According to Parker et al. [41], and supported by Ciaian et al. [42] using Keynesian speculative demand theories, these interactions are important in shaping Bitcoin's price dynamics, where market liquidity and transaction costs play essential roles in price stability and fluctuations.

Exploring the effect of different economic metrics on cryptocurrency prices, Lyons [43] employed the microstructure approach that emphasizes the asymmetry in market information and how order flows—measured as the net buyer-initiated orders minus seller-initiated orders—dictate short-term exchange rate movements. This approach is particularly relevant in the Bitcoin market, where bid-ask spreads serve as a proxy for market liquidity, affecting asset prices and expected returns. Dyhrberg et al. [44] and Scaillet et al. [45] demonstrated how these microstructural elements can predict short-term price movements in Bitcoin. Guo et al. [46] further explored this by predicting short-term BTC price fluctuations through analysis of buy and sell orders, highlighting how private information and trading volumes influence bid and ask prices, ultimately impacting market dynamics. Generally speaking, in cryptocurrency markets, unlike traditional stock markets, private information does not pertain to a firm's prospects but rather to the broader market perceptions and trader confidence, which critically influence BTC valuation. The distinction lies in the market's focus on liquidity and speculative trading, driven by the fixed supply of Bitcoin and the speculative nature of its traders. These studies collectively illustrate how traditional economic theories can be adapted to the cryptocurrency context, providing insights into both the predictability and the inherent uncertainties of these digital assets. The ongoing challenge lies in integrating these economic models with real-time market data to enhance the accuracy and relevance of cryptocurrency price predictions.

B. STATISTICAL MODELS

Statistical models are mathematical frameworks used to make quantifiable predictions based on statistical assumptions and processes. In the context of financial markets, these

TABLE 1. Key terms in cryptocurrency price prediction and trading strategies.

Task	Term	Description
Price Prediction	**Price Prediction Model**	Techniques used to estimate future prices based on certain types of cryptocurrency-related data. In cryptocurrency markets, these models must account for unique factors such as high volatility and market sentiment, which can dramatically influence price movements.
	Technical Analysis	Involves studying historical price and volume data to predict future market behavior. This analysis often uses indicators such as moving averages, RSI, and Bollinger Bands to identify trends and potential price points.
	Fundamental Analysis	Examines macroeconomic indicators, market conditions, and political events that could affect the value of cryptocurrencies. Unlike traditional markets, fundamental analysis of cryptocurrencies may also consider technological advancements and regulatory changes.
	Quantitative Analysis	Uses mathematical models to predict price movements based on quantitative data. Techniques include statistical regression models, machine learning algorithms, and Monte Carlo simulations, which are particularly useful in handling the complex dynamics of cryptocurrency markets [21].
	Sentiment Analysis	Analyzes market sentiment expressed through social media, news trends, and market commentary to gauge investor attitudes and potential market moves. This method has gained prominence with the rise of digital communication and its impact on cryptocurrency trading [75].
Trading Strategy	**Cryptocurrency Trading**	The act of speculating on cryptocurrency price movements via a trading platform, or buying and selling the underlying coins via exchanges.
	Exchanges	Platforms where traders buy, sell, or exchange cryptocurrencies for other digital currency or traditional currency like US dollars or Euro. Examples include Coinbase, Binance, and Kraken [22].
	Trading Pairs	Refers to two currencies that are being traded against each other. For example, in the trading pair BTC/USD, Bitcoin can be bought using US dollars.
	Transaction Fees	Fees charged by exchanges for facilitating trades, which can vary widely between platforms and types of transactions [12].
	Trading Signals	These are recommendations or strategies to buy or sell a specific cryptocurrency at a specific time and price, often generated by analysis or automated trading algorithms [23].
	Wallets	Digital tools that allow users to store and manage their cryptocurrency holdings. Wallets can be "hot" (connected to the internet) or "cold" (offline storage options), providing different levels of security [24].
	Trading Strategies	Methods or approaches used by traders to decide when to buy and sell cryptocurrencies. For example, day trading [25], swing trading [26], scalping [27], etc.
	Volatility	The measure of the price variations at which a cryptocurrency trades over a certain period. High volatility in cryptocurrency markets indicates substantial price swings, providing opportunities and risks for traders. Understanding volatility is crucial for managing risk and strategy planning. High-volatility markets can offer significant gains but also present an increased risk of losses [28].
	Market / Limit Order	Market orders are transactions meant to execute as quickly as possible at the current market price. Limit orders are set to execute only at a specific price or better [29].

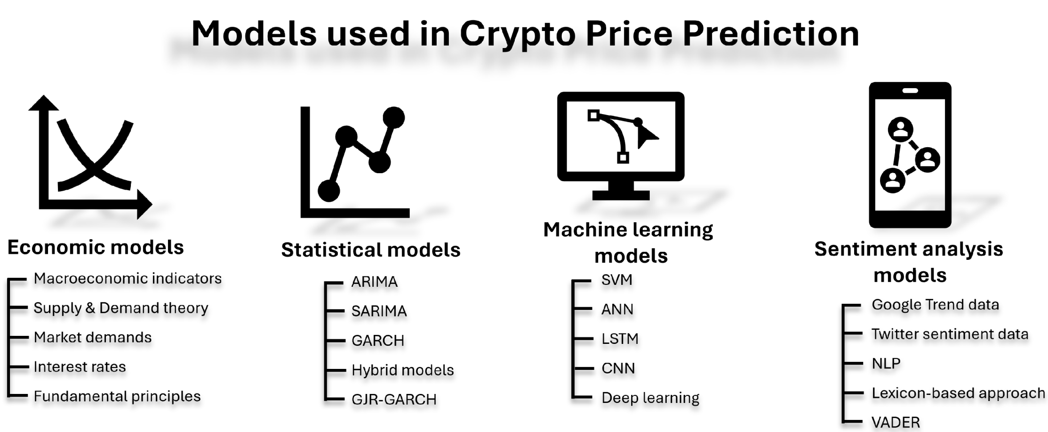

FIGURE 3. The diagram categorizes price predictive models into economic, statistical, machine learning, and sentiment analysis models, highlighting their respective contributions and applications in the field.

models analyze historical data to identify trends, patterns, and relationships that can be used to forecast future market behaviors. The logic underlying the use of statistical models in cryptocurrency price prediction is rooted in the assumption that historical price movements and volatility can provide insights into future trends [47]. The core idea behind applying statistical models to cryptocurrency prices is the Efficient Market Hypothesis (EMH), which suggests that asset prices reflect all available information. However, in the volatile and somewhat unpredictable cryptocurrency markets, these models also account for anomalies and market inefficiencies, making them particularly useful for understanding and predicting price dynamics [48].

Several statistical models have proven effective in forecasting cryptocurrency prices, including:

- Autoregressive Integrated Moving Average (ARIMA): Useful for understanding and predicting future values in a series based on its own lags and the lagged forecast errors.
- Exponential Smoothing: This model focuses on smoothing out price data to forecast short-term trends in a more straightforward and adaptable manner.
- Generalized Autoregressive Conditional Heteroskedasticity (GARCH): Best known for modeling financial time series that exhibit volatility clustering—a common phenomenon in cryptocurrency markets.

In recent years, researchers have focused extensively on employing these statistical models to predict the prices of cryptocurrencies, particularly BTC and ETH. These models have been tailored to understand the complex dynamics of these digital currencies, which are influenced by global events, investor sentiment, and market speculations. Nguyen and Le [49] demonstrated that while hybrid approaches incorporating ARIMA and machine learning yielded improved predictive accuracy for BTC price forecasts, they emphasized the importance of traditional statistical models in establishing baseline trends. The ARIMA model, capable of identifying time series patterns, provided valuable insight into future price movements. However, they acknowledged the limitations of this approach, particularly its sensitivity to non-stationary data. A similar effort by Thuan et al. [50] utilized a hybrid ARIMA framework combined with regression and support vector regression (SVR). This approach effectively predicted the closing prices of BTC and ETH, confirming ARIMA's relevance for trend analysis. However, their findings also pointed to the challenges posed by the volatile nature of cryptocurrency markets. The researchers noted that additional external factors, such as macroeconomic indicators, should be integrated into future studies to capture the broader economic context influencing price movements.

Further focusing on the predictive power of pure ARIMA models, Wirawan et al. [51] applied ARIMA (4,1,4) for short-term BTC price forecasts where the numbers are autoRegressive order, differencing order, and moving average order, respectively. Their study revealed that while ARIMA could accurately predict one-day prices with a MAPE of 0.87, it became less accurate over a seven-day horizon (MAPE 5.98). Despite this, ARIMA remained effective for short-term forecasts, though its limitations in long-term prediction highlighted the need for external factors to account for unexpected price swings. In a comparative analysis of different ARIMA models, Yang [52] examined the predictive performance of ARIMA (5,2,1) and ARIMA (0,2,2) models for Bitcoin. They found that ARIMA (0,2,2) offered slightly better short-term forecasting accuracy but recognized that both models struggled to predict sudden price fluctuations. This underscores the challenges faced by statistical models in capturing the inherent volatility of the cryptocurrency market. Azari [53] also emphasized these challenges when assessing Bitcoin price trends over a three-year period using ARIMA. Although ARIMA models effectively identified trends for short-term predictions, their limitations in forecasting long-term fluctuations were evident. He called for further exploration of integrating macroeconomic and technical indicators to enhance prediction accuracy. Overall, these studies collectively highlight the importance of ARIMA for understanding short-term cryptocurrency price trends while acknowledging their challenges in adapting to the volatile and non-stationary nature of cryptocurrency markets.

Beyond ARIMA models, researchers have also employed various other statistical models like GARCH, Seasonal Autoregressive Integrated Moving-Average (SARIMA), and VAR to forecast the price and volatility of cryptocurrencies. Mostafa et al. [54] used a GJR-GARCH model to analyze volatility across ten major cryptocurrencies. Their research highlighted the GJR-GARCH model's ability to capture asymmetry in volatility shocks compared to simpler GARCH models, particularly through Value at Risk (VaR) assessments. The research underlined that conditional variance, derived from the GJR-GARCH model, is an essential indicator of risk that investors and regulators can leverage to optimize portfolio management. Meanwhile, Caporale and Zekokh [55] applied Markov-Switching GARCH models to model the volatility of four major cryptocurrencies. They revealed that traditional GARCH models may inaccurately predict VaR and Expected Shortfall (ES) in cryptocurrency markets due to their inability to handle asymmetries. The Markov-Switching GARCH models better identified volatility patterns under regime shifts, providing a more comprehensive risk assessment tool. Naimy et al. [56] examined several GARCH variants, such as SGARCH, IGARCH, EGARCH, and TGARCH, to evaluate volatility for six leading cryptocurrencies and six major world currencies. Their study demonstrated that advanced GARCH models accounted for volatility clustering and persistent asymmetries across cryptocurrencies, but that the IGARCH model particularly excelled in predicting Monero's volatility. This analysis supports the use of GARCH variants tailored to each cryptocurrency's unique volatility patterns. Ampountolas [57] extended this analysis by using both univariate and multivariate GARCH models to assess high-frequency volatility spillovers among BTC, ETH, LTC, and Ripple. The GJR-GARCH model (1,1) provided superior predictive accuracy in all horizons, while the multivariate DCC-GARCH model highlighted cross-market volatility shocks and bidirectional spillovers between the cryptocurrencies. This finding underscores the interconnectedness of these markets. Gao et al. [58] integrated GARCH with Long-Short Term Memory (LSTM) neural networks in a hybrid approach. Their study showed that combining these models led to enhanced predictive performance, particularly for highly volatile data with limited historical sequences. Similarly, Shen and Wang [59] utilized GARCH and ARIMA alongside machine learning models like XGBoost and LightGBM. While GARCH and ARIMA struggled during highly volatile events like COVID-19, machine learning approaches provided promising predictive capabilities in cryptocurrency markets. Finally, Kristjanpoller and Minutolo [60] proposed a hybrid ANN-GARCH framework for forecasting Bitcoin's volatility. Their preprocessing steps incorporated technical analysis and principal component analysis (PCA), enabling their model to capture non-linear dynamics efficiently. Meanwhile, Roy [61] demonstrated that GARCH-EVT models with skewed distribution significantly improved intraday VaR and ES predictions for BTC, ETH, LTC, and Binance Coin, underscoring the predictive power of GARCH models combined with Extreme Value Theory.

These studies collectively emphasize the importance of statistical models and their variants in understanding the complex volatility structures of cryptocurrency markets. Such models remain vital for managing market risks and achieving more accurate price forecasts, particularly when tailored to account for regime shifts, asymmetry, and spillover effects. Incorporating statistical models with machine learning and deep learning techniques offers promising avenues for further enhancing predictive performance.

C. MACHINE LEARNING MODELS

The application of machine learning in cryptocurrency price prediction is increasingly gaining traction due to the market's volatility, non-stationary nature, and intricate patterns. Recent literature shows diverse models, from classic regression to deep learning, combined with feature selection techniques for data preprocessing. Akyildirim et al. [62] employed SVM, logistic regression (LR), artificial neural networks (ANNs), and random forests (RFs) to predict cryptocurrency returns using past price and technical indicators. Despite fluctuating accuracy levels across algorithms, they achieved 55-65% predictive accuracy on average, with SVMs outperforming the others. Expanding on ANN-based models, Ye [63] explored how a three-layer feedforward ANN could be applied to forecast daily price movements for BTC, ETH, and Cardano (ADA). He achieved 61-65% prediction accuracy by preprocessing nine technical indicators and converting them into discrete trends. Forward Selection and Backward Elimination further improved model performance. Julianto et al. [64] also emphasized these feature selection techniques, confirming that Neural Networks yield optimal RMSE when combined with Backward Elimination. These studies underscored the role of technical indicators in ANN-based models, although they lacked a comparative analysis with more advanced deep learning techniques. Lyu [65] expanded ML studies beyond a single currency by comparing ten models across ten cryptocurrencies, finding Gradient Boosting to excel with statistical metrics like mean squared error (MSE). Decision Tree and RF algorithms performed well for certain currencies, but further exploration could yield more accurate models.

Deep learning approaches have proven their importance in uncovering non-linear relationships and hidden patterns within the cryptocurrency markets. Thavaneswaran et al. [66] demonstrated this by employing feedforward neural networks and statistical bootstrapping to predict cryptocurrency prices. Their hybrid model produced accurate prediction intervals through bootstrapping deep learning models, leveraging neural networks' ability to handle non-linear data. In a similar vein, Lahmiri and Bekiros [67] corroborated these findings using Long Short-Term Memory (LSTM) networks. Their approach outperformed traditional neural architectures by effectively modeling chaotic market dynamics. Liu et al. [68] further strengthened the case for deep learning by applying stacked denoising autoencoders (SDAE) in Bitcoin price prediction. The SDAE model surpassed backpropagation neural networks (BPNN) and support vector machines (SVM), achieving better directional and level forecasting metrics. Similarly, Priya et al. [69] reinforced the strength of LSTM models for cryptocurrency prediction by comparing their performance against regression-based and traditional neural network approaches. Although computationally intensive, the LSTM model accurately captured long-term dependencies that other models struggled to handle. Complementing the work on LSTM networks, Wu [70] examined convolutional neural networks (CNN) to forecast cryptocurrency prices based on intrinsic interrelationships among currencies. His research showed CNNs to be more accurate than K-Nearest Neighbor (KNN) and linear regression. By incorporating end-to-end learning strategies and parameter optimization, the CNN model captured complex interdependencies between currencies. Alamery [71] expanded this comparative analysis by assessing multiple machine learning models, including linear regression (LR), decision tree (DT), random forest (RF), SVM, and CNN. The results showed CNNs as the most effective in predicting Bitcoin prices, while RF proved the best-performing machine learning model overall. Despite these findings, the study raised concerns about the reliance on Kaggle data, which may limit generalizability. Jay et al. [72] offered a unique approach using stochastic neural networks to forecast BTC, ETH, and Litecoin prices, integrating random walk theory into multi-layer perceptron (MLP) and LSTM models. By simulating market volatility through layer-wise randomness, their stochastic model consistently outperformed deterministic models in handling the chaotic dynamics of cryptocurrency markets. Mallqui and Fernandes [73] took feature selection techniques further by combining them with artificial neural networks (ANN), support vector machines (SVM), and ensemble models for BTC price prediction. Their use of both regression and classification approaches improved directional accuracy by over 10%, demonstrating the value of comprehensive feature

TABLE 2. Taxonomy of works studied price prediction task.

Models	Data Type	Methods
Economic Models	Historical price and volume data, crypto-returns, market data, liquidity metrics, transaction costs, buy and sell orders, interest rates, US bond yields, non-exchange transactions.	Macroeconimic factors ([38], [39]), Supply and Demand theory [40], Keynesian speculative theory ([41], [42]), Microstructural elements ([43], [44], [45], [46])
Statistical Models	Daily closing price, volatility data, high-frequency intraday price data.	ARIMA [49], hybrid ARIMA and SVR [50], ARIMA [51], ARIMA (0,2,2) [52], GJR-GARCH [54], Markov-Switching GARCH [55], IGARCH [56], DCC-GARCH [57], GARCH and LSTM [58], GARCH and ARIMA [59], ANN-GARCH [60], GARCH-EVT [61]
Machine Learning Models	Historical price, technical indicators, intraday market data, daily exchange rate, intrinsic interrelationships among currencies.	SVM [62], ANN [63], Forward Selection and Backward Elimination [64], Gradient Boosting [65], Feedforward NN and statistical bootstrapping [66], LSTM [67], SDAE [68], LSTM [69], CCNN [70], CNN and Random Forest [71], MLP and LSTM [72], ANN and SVM [73], BART [74]
Sentiment Analysis Models	Historical price data, Twitter sentiments, BTC to ETH trade data, Twitter activity data, Google Trends data, Telegram sentiment data, high-frequency trading data, various financial metrics.	DRL [77], Q-learning [78], Granger causality testing [79], NN [80], VAR [81], Google trends and Twitter sentiment data [82], LSTM [83], Telegram and Google trends data [84], DL-GuesS [85], RNN and LSTM [86], LSTM [87], KNN and CART [88], LSTM and Regression model ([89], [90]), DNN [91]

selection. To build on this, Derbentsev et al. [74] employed a Binary Auto Regressive Tree (BART) model to forecast the prices of BTC, ETH, and Ripple. By combining ARIMA with BART, they developed a hybrid model that effectively improved short-term forecasts and outperformed traditional time-series models.

Overall, these studies underscore that deep learning, ensemble methods, and feature selection techniques offer promising directions in cryptocurrency forecasting, despite challenges like high volatility and non-stationary data. Future research should continue to refine these models and explore the integration of new features to enhance predictive accuracy further.

D. SENTIMENT ANALYSIS MODEL

Sentiment analysis, often referred to as opinion mining, is a field of study that analyzes people's sentiments, opinions, and emotions through digital text. In the context of financial markets, and particularly cryptocurrencies, the sentiments extracted from various online platforms can significantly influence market movements. This is because public sentiment often reflects underlying attitudes toward current and future financial prospects, thereby affecting trading behaviors [75]. This technique utilizes natural language processing (NLP) and machine learning to systematically identify, extract, and quantify affective states and subjective information from textual sources. In the realm of cryptocurrencies, platforms such as Twitter, Reddit, and other social media are mined to gather public sentiment. The computational process involves collecting vast amounts of data, preprocessing text for analysis, and applying algorithms that can gauge the emotional tone behind words to predict potential market shifts [76].

Several tools and algorithms are employed for sentiment analysis, including:

- Lexicon-based approaches, which classify words in a text as positive or negative based on a predefined sentiment lexicon.
- Machine learning models, which learn to classify sentiment from large datasets, often using methods such as SVM or deep learning techniques like neural networks.

Among other price-predicting models, sentiment-based models have gained considerable traction over recent years. Multiple studies have demonstrated their potential to improve forecasts, particularly for leading cryptocurrencies such as BTC, ETH, and LTC [77], [78]. By analyzing investor sentiment on platforms like Twitter and Reddit, researchers can uncover market trends and better predict price movements. The advantage here is twofold: sentiment analysis captures the emotional pulse of the market, and it provides insights that are not immediately apparent through traditional data analysis methods.

To explore Twitter sentiment analysis to forecast BTC, LTC, and Bitcoin Cash (BCH), Kraaijeveld and De Smedt [79] used a cryptocurrency-specific lexicon-based sentiment analysis approach combined with financial data and Granger causality testing. They found significant predictive power in Twitter sentiment for BTC, BCH, and LTC price movements but identified gaps due to the prevalence of Twitter bots, which distort genuine sentiment signals. Similarly, Valencia et al. [80] incorporated Twitter data into machine learning models, including neural networks (NN), support vector machines (SVM), and random forests (RF). They discovered that NNs outperformed the others in directional accuracy for BTC, ETH, LTC, and XRP. However, they emphasized the need for comprehensive social data integration and real-time sentiment analysis. Alipour and Charandabi [81] took a different approach using regression and vector autoregression (VAR) to analyze BTC and ETH volatility. They highlighted the varying

TABLE 3. Detailed summary of selected papers for Bitcoin price prediction.

Model	Ref	Pros	Cons
Economic	Dutta *et. al.* [38]	Uses advanced models (GRU, LSTM) to enhance prediction accuracy by capturing complex economic patterns. Integrates various economic factors, demonstrating financial gains through optimized trading strategies.	Focus on short-term predictions might not address long-term trends, and reliance on historical economic data struggles to adapt to future changes.
	Conrad *et. al.* [40]	Employs GARCH-MIDAS to separate volatility components, showing the impact of S&P 500 and Baltic Dry Index on Bitcoin volatility. Provides a comprehensive framework for long-term prediction.	Model complexity might limit accessibility. Findings based on a short sample period could affect long-term applicability and robustness.
	Cianian *et. al.* [42]	Examines interdependencies between Bitcoin and altcoins, highlighting global macro-financial impacts on cryptocurrency prices. Offers a detailed economic perspective on price formation.	Focuses on data from 2013-2016, limiting generalizability. Complex methods may be less accessible to those without a strong econometric background.
	Dyhrberg *et. al.* [44]	Analyzes Bitcoin liquidity and transaction costs, showing it is investible at the retail level. Provides insights into trading activity and intraday patterns.	Focuses on high-frequency data, possibly missing broader economic factors. Primarily addresses retail trading, overlooking institutional behaviors.
	Scaillet *et. al.* [45]	Uses high-frequency data to analyze Bitcoin price jumps, detailing market conditions and the role of liquidity and order flow in predicting jumps.	High-frequency focus limits applicability to long-term modeling. Reliance on Mt. Gox data (2011-2013) may affect relevance to current markets.
Statistical	Thuan *et. al.* [50]	Combines ARIMA with LSTM and SVR to enhance cryptocurrency price prediction, effectively leveraging the strengths of statistical and machine learning models.	The complexity of integrating multiple models could pose implementation challenges.
	Mostafa *et. al.* [54]	Combines GJR-GARCH with NIG distribution for accurate volatility estimation, capturing fat tails and extreme risks. Uses ANNs for prediction, showing higher precision than ARIMA in some cases, and provides a robust framework for risk and forecasting.	Focus on the top ten cryptocurrencies might limit applicability to others. Reliance on historical data (2018-2020) may affect future relevance.
	Gao *et. al.* [58]	Combines LSTM with GARCH to handle Bitcoin's high volatility, improving prediction by capturing non-stationary and nonlinear dynamics.	LSTM-GARCH model's complexity might pose challenges for implementation. The study focuses on Bitcoin, which may limit applicability to other cryptocurrencies.
	Kristjanpoller *et. al.* [60]	Integrates GARCH models with PCA of technical indicators, enhancing volatility prediction accuracy for Bitcoin over traditional models.	Using PCA adds complexity, potentially limiting accessibility. The focus on volatility prediction rather than direct price forecasting could reduce broader applicability.
	Roy [61]	Utilizes GARCH-EVT for intraday risk prediction, capturing extreme values and fat-tailed behavior in cryptocurrency returns effectively.	The complexity of combining GARCH with EVT might limit accessibility. The focus on high-frequency data and a specific volatile period may not address long-term trends.
Machine Learning	Akyildirim *et. al.* [62]	Analyzes predictability of twelve cryptocurrencies using machine learning models, with SVMs showing the best and consistent results. Demonstrates high accuracy in predicting short-term price movements.	Performance varies across different cryptocurrencies, and the focus on machine learning models may limit accessibility for those unfamiliar with these techniques. Applicability to long-term predictions is limited.
	Ye *et. al.* [63]	Employs ANNs for predicting price direction of Bitcoin, Ethereum, and Cardano, showing high accuracy. Captures complex patterns effectively.	Focuses on a few cryptocurrencies, limiting broader applicability. Reliance on historical data may affect future adaptability.
	Liu *et. al.* [68]	Uses stacked denoising autoencoders (SDAE) for Bitcoin price prediction, achieving higher accuracy compared to traditional models like BPNN and SVR. Effectively handles directional and level prediction.	The deep learning model's complexity may limit accessibility for those without a background in deep learning. The study primarily focuses on Bitcoin, reducing generalizability to other cryptocurrencies.
	Alamery [71]	Evaluates a range of machine learning models, with Random Forest and CNN showing superior performance for daily Bitcoin price prediction. Comprehensive comparison enhances understanding of model effectiveness.	The extensive comparison of models adds complexity, potentially overwhelming some users. The focus is primarily on Bitcoin, which may limit applicability to other cryptocurrencies.
	Jay *et. al.* [72]	Combines stochastic processes with neural networks to enhance prediction accuracy for cryptocurrency prices, addressing the market's erratic behavior and volatility.	The use of advanced stochastic neural networks can be complex, making it less accessible for non-experts. The focus on technical complexity might overshadow practical implementation details.
Sentiment Analysis	Otabek *et. al.* [78]	This study leverages Q-learning to optimize the selection of tweet attributes, significantly reducing computational resources while maintaining high prediction accuracy.	The model's effectiveness is contingent on the quality and relevance of the selected tweet attributes, which may vary over time.
	Alipour *et. al.* [81]	The paper effectively combines sentiment analysis with vector autoregression to predict price volatility, offering a nuanced understanding of the relationship between social media activity and market fluctuations.	The study requires extensive computational resources, which may not be feasible for all researchers or practitioners.
	Feizan *et. al.* [83]	The use of weighted sentiment scores based on the influence of Twitter users enhances the model's relevance and predictive power.	The model's reliance on Twitter sentiment may introduce biases, as not all relevant market participants are active on social media.
	Ansari *et. al.* [90]	The paper highlights the use of historical price data and various economic indicators, offering a comprehensive approach to cryptocurrency price forecasting.	The reliance on historical data may limit the model's ability to adapt to rapid market changes. The study does not account for the influence of other external factors, which can significantly impact cryptocurrency prices.

impact of sentiment measures on BTC and ETH volatility, emphasizing the importance of refined sentiment analysis techniques. Wolk [82] combined Google Trends data with Twitter sentiment to predict BTC prices, finding significant correlations between social media sentiment and short-term BTC price fluctuations. He noted that market perceptions affect speculative cryptocurrency prices and suggested exploring search volume as a complement to sentiment analysis. Feizian and Amiri [83] advanced sentiment analysis by assigning weightings based on user influence factors. Their machine learning model, which employed LSTM, improved prediction accuracy for BTC, ETH, EOS, and other cryptocurrencies. They argued that influence-weighted sentiment scores provided a more accurate depiction of market behavior. Smuts [84] compared Telegram and Google Trends data, finding Telegram more accurate for predicting BTC price trends. His LSTM model showed that deep learning models could capture behavioral finance signals, stressing the importance of diversifying data sources to handle volatility.

Other studies, such as, Parekh et al. [85] and Fernandes et al. [86] also explored the potential of deep learning models for incorporating sentiment data. Parekh proposed a hybrid DL-GuesS model that relied on sentiment data and price histories of multiple cryptocurrencies, including Dash and LTC. Fernandes integrated Reddit and Twitter sentiment into Recurrent Neural Network (RNN) and LSTM models to provide accurate BTC forecasts. Prajapati [87] emphasized the predictive importance of Google News alongside Reddit sentiment, showing that his LSTM model could effectively predict BTC prices using news and social sentiment analysis. Chen [88] explored high-frequency trading with Twitter data, combining KNN and CART models with a portfolio optimization approach to refine trading strategies. Uras et al. [89] and Ansari and Vani [90] focused on cryptocurrency closing prices using LSTM and linear regression models. They found significant correlations between historical market data and sentiment measures, though they called for integrating more features. Chatterjee et al. [91] analyzed correlations between BTC, ETH, and LTC using deep neural networks (DNN), reinforcing the importance of understanding cryptocurrency interdependencies. Throughout this section, we have explored a range of predictive models, each offering unique perspectives and methodologies for forecasting cryptocurrency prices. Table 2 provides general information on reviewed studies that are explained in this section, outlining the dataset and key algorithms/methods used.

From economic models that apply traditional theories such as supply and demand to the nuances of digital currencies, to statistical models like ARIMA and GARCH that capture the time-series nature of market data, each approach provides valuable insights. Moreover, the exploration into machine learning models reveals the power of advanced computational techniques in handling the complexity and volatility inherent in cryptocurrency markets. Additionally, sentiment analysis has been highlighted as an effective tool for extracting market mood from vast amounts of unstructured data from social media and news sources. The integration of sentiment analysis with machine learning techniques represents a particularly promising approach. By combining the quantitative precision of machine learning models with the qualitative insights of sentiment analysis, we can achieve a more holistic and robust framework for cryptocurrency price prediction. This synergy enables a deeper understanding of market dynamics and potentially enhances the accuracy of predictions by leveraging diversified data sources. It is evident that the integration of multiple predictive models, particularly the fusion of sentiment analysis with machine learning, holds substantial promise for advancing our ability to forecast cryptocurrency prices more effectively and with greater confidence. To gain a better understanding of the reviewed papers, we have selected a few from each model and described their pros and cons in Table 3.

E. EVALUATION METRICS

In this subsection, we will summarize the various evaluation metrics employed to assess the performance of price-prediction models.

1) **Mean Absolute Error (MAE)**. MAE is a commonly used metric for evaluating the accuracy of a model's predictions. It is valued for its simplicity, as it represents the average of the absolute differences between the predicted values and the actual observed values [30]. The formula to compute MAE is:

$$\mathrm{MAE} = \frac{1}{n}\sum_{t=1}^{n} |AP_t - PP_t|, \tag{1}$$

where AP_t represents the actual price at time t and PP_t represents the predicted price at time t. and number of experiment entities (e.g. minutes, hours, days) is represented as n.

2) **Root Mean Square Error (RMSE).** This metric is often used to assess the difference between the model's predicted values and the observed values [31]. It is calculated using the following formula:

$$\mathrm{RMSE} = \sqrt{\frac{\sum_{t=1}^{n}(AP_t - PP_t)^2}{n}}. \tag{2}$$

The RMSE value is always non-negative, with lower values indicating more accurate predictions.

3) **Coefficient of Determination (R^2).** The R^2 metric is used to assess the accuracy of forecast outputs, indicating how well the observed outcomes are replicated by the model [32]. It is calculated using the following formula:

$$R^2 = 1 - \frac{RSS}{TSS}, \tag{3}$$

where RSS is the residual sum of squares, defined as $RSS = \sum_{t=1}^{n}(AP_t - PP_t)^2$, and TSS is the total sum of squares, defined as $TSS = \sum_{t=1}^{n}(AP_t - \overline{AP})^2$ where, $\overline{AP}$ represents the average actual price over the time period ($1 \leq t \leq n$). The R^2 value ranges from 0 to 1, with 1 indicating a perfect alignment between the predicted and actual data.

4) **Mean Absolute Percentage Error (MAPE).** MAPE is also utilized to assess the prediction accuracy, much like the above-mentioned metrics. More preciesly, MAPE is often employed as a loss function in model evaluation due to its clear and intuitive interpretation of relative error [33]. It is formally calculated as follows:

$$\text{MAPE} = \frac{1}{n}\sum_{t=1}^{n}\left|\frac{AP_t - PP_t}{AP_t}\right| \times 100\%. \tag{4}$$

5) **Positive Predictive Value (PPV).** PPV is a metric used to evaluate the accuracy of a classification model in the context of price prediction. Specifically, it measures the proportion of predicted positive price movements that are true positives. This metric is particularly useful in assessing the performance of models in predicting upward price movements accurately [34]. The formal computation is given by:

$$\text{PPV} = \frac{TP}{TP + FP}, \tag{5}$$

where TP represents the number of true positives (instances where the model correctly predicted a price increase) and FP represents the number of false positives (instances where the model predicted a price increase, but the price did not actually increase).

6) **Negative Predictive Value (NPV)** Unlike PPV, this metric specifically measures the proportion of predicted negative price movements that are true negatives. This metric is particularly useful in assessing the performance of models in predicting downward price movements accurately [34]. The formal computation is given by:

$$\text{NPV} = \frac{TN}{TN + FN}, \tag{6}$$

where TN represents the number of true negatives (instances where the model correctly predicted a price decrease) and FN represents the number of false negatives (instances where the model predicted a price decrease, but the price did not actually decrease).

IV. CRYPTOCURRENCY TRADING STRATEGIES

Trading strategies in the cryptocurrency market merge disciplines from finance, data science, and computational technology to address one of the most rapidly evolving financial arenas. As cryptocurrencies increasingly become a staple in global financial systems, developing and implementing robust trading strategies is essential for both seasoned traders and institutional investors. This section delves into the sophisticated techniques employed to navigate the complexities of cryptocurrency trading, offering a detailed examination of both traditional and innovative approaches.

Technical Analysis and Algorithmic Trading stand out as two pivotal strategies that leverage historical data and cutting-edge technology to optimize trading outcomes. Through technical analysis, traders interpret historical price movements and volume trends to forecast future market behavior, employing tools such as indicators and chart patterns that signal entry and exit points. On the other hand, algorithmic trading uses algorithms and AI to execute trades at superhuman speeds and accuracy, constantly adapting to new data to refine trading decisions [92]. Figure 4 depicts the integration of traditional and modern approaches in cryptocurrency trading strategies.

A. TECHNICAL ANALYSIS

Technical analysis is a trading discipline employed to evaluate investments and identify trading opportunities by analyzing statistical trends from trading activity, such as price movements and volume. Unlike fundamental analysis, which looks at economic and financial factors to estimate the intrinsic value of a security, technical analysis focuses exclusively on price and volume data [20].

The primary logic behind technical analysis is that all current market information is already reflected in the price, which means that studying price action is all that is required. Under this paradigm, patterns from the past will often indicate future potential behavior. This method is particularly useful in the cryptocurrency market due to its high volatility and the frequency of trend-based movements [93]. Analysts believe that by identifying patterns and continuities in price behavior, they can predict future price movements with a reasonable degree of accuracy. Several technical indicators are essential for traders looking to harness and interpret cryptocurrency market data:

- Moving Averages (MA): Useful for smoothing out price data to identify trends [94].
- Relative Strength Index (RSI): Helps gauge the speed and change of price movements, indicating overbought or oversold conditions [95].
- Moving Average Convergence Divergence (MACD): A momentum indicator that shows the relationship between two moving averages of prices [96].

In recent years, the complexity of cryptocurrency markets has spurred researchers to refine and optimize trading strategies using advanced technical indicators. These studies collectively aim to enhance the predictive accuracy and profitability of trading strategies across various cryptocurrencies like Bitcoin, Ethereum, and Litecoin. For example, Cohen [97] examined the applicability of RSI and MACD for Bitcoin trading, finding that while RSI underperformed a simple buy-and-hold strategy, MACD demonstrated significant potential when optimized with particle swarm optimization (PSO). This contrast between the effectiveness of different technical indicators prompted further inquiry into optimal parameter settings and strategy configurations. Cohen's work laid the groundwork by demonstrating the potential of optimized technical indicators to outperform traditional

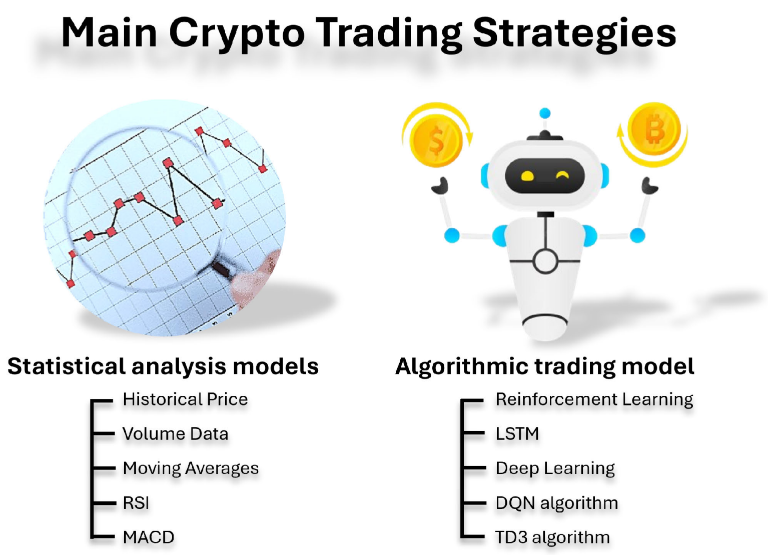

FIGURE 4. A representation of the main trading strategies in cryptocurrency markets: technical analysis with modern algorithmic trading, and algorithmic trading model in formulating effective trading strategies.

trading methods. Building on the notion of optimization, Deac and Iancu [98] employed a genetic algorithm (GA) to optimize the parameters of MACD and RSI strategies further. Their methodology highlights the importance of hyper-parameter tuning in maximizing the efficacy of technical indicators. By applying GA to optimize these strategies on a different asset class, their research not only supports Cohen's findings but extends them by showcasing the adaptability and effectiveness of genetic algorithms in refining trading strategies across diverse markets. Transitioning from theoretical optimization to practical application, Bitto et al. [99] utilized a combination of machine learning models and technical indicators (MA and RSI) to predict cryptocurrency prices. Their study emphasizes the practical implications of technical indicators in real-world trading scenarios. They found that AR models, when combined with MA and RSI, offered high predictive accuracy, thus validating the potential of integrating traditional technical analysis with newer computational techniques to enhance trading strategies.

The exploration of optimal combinations of technical tools was furthered by Cohen and Qadan [100], who investigated the use of multiple technical indicators for trading cryptocurrencies. Their research identified that different combinations work best for different cryptocurrencies and trading styles, such as swing trading versus intraday trading. This study underlines the necessity of tailoring technical strategies to specific market conditions and asset characteristics, reinforcing the findings from earlier studies about the importance of customization in trading strategies. Meanwhile, Xu et al. [101] introduced a multistage dynamic trading model that combines the Gray Model and ARIMA with MACD and the Sharpe ratio, pushing the boundaries of hybrid trading strategies. Their model, which was tested on volatile assets like Bitcoin and gold, illustrates the effectiveness of combining traditional and modern forecasting techniques to manage risk and enhance profitability in highly volatile markets. Finally, Naganjaneyulu et al. [102] provided a novel approach by developing hierarchical strategies using a mix of trend and momentum indicators, including EMA and RSI, tailored to specific market scenarios. Their work not only supports the findings of Cohen *et. al.* regarding the effectiveness of tailored indicator combinations but also adds a new dimension by emphasizing the importance of hierarchical and scenario-specific strategies.

These studies collectively enhance our understanding of the sophisticated techniques used in cryptocurrency trading and underline the ongoing need for research into optimizing and integrating various technical indicators and trading strategies. The logical progression from the basic application and optimization of individual indicators to the integration and hybridization of multiple models and indicators demonstrates a clear path toward improving the effectiveness and profitability of cryptocurrency trading strategies. Continuing from the previous analysis of trading strategies in the cryptocurrency market, we further explore the use of technical indicators and optimization methods to develop profitable strategies. A critical contribution comes from Lin et al. [103], who investigated the application of technical indicators, including MA, MACD, and RSI, in combination with machine learning models such as SVM, eXtreme Gradient Boosting (XGBoost), and LSTM. They aimed to evaluate the feasibility of machine learning models in enhancing trading strategies based on technical indicators.

Their study reinforced earlier findings by showing that models like XGBoost could outperform conventional trading strategies, particularly by leveraging technical indicators and news sentiment analysis. However, incorporating news sentiment data did not significantly improve predictive performance. Similarly, Jain et al. [104] examined Bitcoin trading strategies using multiple technical analysis tools such as MA, MACD, RSI, and Bollinger Bands. Their research confirmed that technical indicators could identify entry and exit points, allowing traders to generate significantly positive returns. This study aligns with previous findings regarding the practical utility of technical analysis in cryptocurrencies and extends them by providing insights into how multiple indicators can be combined to detect market signals, resulting in bullish or bearish strategies. Wijaya et al. [105] focused on the effectiveness of RSI and MACD on stock performance. Their study, which employed Debt to Equity Ratio (DER) as a moderating variable, highlighted the positive impact of both indicators on stock performance. By emphasizing the importance of market conditions, their work supports the conclusion of Bitto *et. al.* regarding the necessity of combining technical analysis with broader market metrics to yield reliable predictions. Additionally, their identification of DER as a moderating factor offers a new dimension to consider when refining trading strategies. Meanwhile, Metghalchi et al. [106] introduced a new perspective by combining a simple exchange-traded fund (ETF) portfolio with well-known technical trading rules (TTRs). Applying MA, RSI, and MACD to the portfolio, they compared their risk-adjusted performance against balanced funds and market benchmarks. Their study showed that these TTRs provided superior performance, suggesting that even simple portfolios can benefit from applying technical indicators. Collectively, these studies reinforce the critical role of optimizing technical indicators and machine learning models to maximize trading profitability in cryptocurrency markets. They also underscore the importance of refining strategies through comprehensive backtesting and considering broader financial metrics.

After exploring the various optimization strategies, we expand our review with a set of studies on the fusion of traditional statistical methods and machine learning approaches in trading strategies. Song and Zhang [107] initiated this thread by employing the ARIMA model to predict the prices of Bitcoin and Ethereum. They then combined this with the analytic hierarchy process (AHP) and particle swarm optimization (PSO) to devise a comprehensive trading strategy. This layered approach effectively linked statistical modeling and optimization techniques, underscoring the benefits of incorporating AHP's structured decision-making framework. The result was a more accurate trading strategy, one that leveraged ARIMA's strengths and AHP-PSO's efficiency. Similarly, the idea of hybrid strategies was extended by Lei et al. [108], who recognized the limitations of the traditional MACD indicator in handling complex price trends. They enhanced the MACD strategy by blending it with deep learning through residual networks, creating the MACD-KURT strategy. By applying machine learning models, they found that deep learning could refine the identification of trading points, improving accuracy and profitability. Their work naturally builds upon Song and Zhang [107] by addressing the limitations of statistical methods and highlighting the adaptability of deep learning networks to market complexities. The power of machine learning strategies was further corroborated by Sebastião and Godinho [109], who devised ensemble models for trading Bitcoin, Litecoin, and Ethereum. Their use of linear regression, SVM, and random forests aligns with Lei *et. al.* 's exploration of model integration, further emphasizing the necessity of combining diverse models to handle various market scenarios. This ensemble approach ensured consistent profitability across changing market conditions.

Building on the ensemble modeling concept, Rustam et al. [110] proposed combining technical indicators such as MACD and RSI with fuzzy logic methods to guide trading decisions. Their approach relied on fuzzy logic to filter out false signals and handle market noise effectively, achieving impressive prediction accuracy. This methodological approach adds value by emphasizing the importance of robust signal filtering, which aligns with the predictive models presented by Khandelwal and Sebastião.

B. ALGORITHMIC TRADING

Algorithmic trading, powered by Artificial Intelligence (AI), has become a cornerstone in modern financial markets, including cryptocurrencies like BTC, ETH, and LTC. AI trading leverages algorithms to execute trades based on predefined criteria and adaptive learning mechanisms that analyze vast datasets much quicker and more efficiently than human traders. This capability enhances the speed and accuracy of trading decisions. In addition to that, it adapts dynamically to new data and provides a significant edge in the volatile cryptocurrency market. The importance of AI in trading stems from its ability to digest and interpret complex market data to identify trading opportunities, manage risks, and optimize the execution of trades. By integrating various machine learning models, such as deep learning and reinforcement learning, AI systems can learn from market patterns and improve their predictive accuracy over time. This iterative learning process is crucial for adapting to the ever-changing market conditions typical of the cryptocurrency markets.

In recent work, Agarwal et al. [111] explore several state-of-the-art ML algorithms to analyze cryptocurrency trends for BTC, ETH, and LTC. Their study leverages historical data, including price and volume, to predict future market values. The researchers highlight the effectiveness of machine learning in capturing complex patterns in cryptocurrency markets, which traditional methods cannot easily replicate. However, they note the need for more granular real-time data to improve the models' responsiveness to market changes. Following this analysis, Al Hawi et al. [112] examined the application of various machine learning algorithms — SVM, KNN, and Light Gradient Boosted Machine (LGBM)—to predict the price movements of cryptocurrencies such as BTC, ETH, and LTC. Their study not only employed these algorithms but also performed sensitivity analysis to evaluate different parameter settings, enhancing the model's accuracy and responsiveness to market dynamics. The researchers found that KNN exhibited the highest forecasting performance overall, indicating the potential of this method in real-time trading scenarios. However, they noted that while SVM and LGBM offered considerable accuracy, their performance varied significantly across different cryptocurrencies, suggesting the need for tailored approaches for each digital currency. The study underscores the necessity of ongoing research to refine these algorithms further and to explore additional factors that might impact cryptocurrency prices, such as social media influence and global economic indicators.

Building on the idea of resilience, Suliman et al. [113] introduce a deep reinforcement learning algorithm, Duelling DQN, designed to maximize short-term profits by learning optimal trading actions based on historical price movements. The authors critically analyze the model's ability to adapt to real-time prices and conclude that while the AI algorithm performs well against traditional strategies, it requires enhancements to handle the high volatility inherent in cryptocurrency markets more effectively. In a similar vein, Ma et al. [114] implement a Deep Q-Learning framework for trading cryptocurrencies. Their research tests the algorithm across thousands of episodes, showcasing its potential to generate substantial returns. However, they acknowledge the model's high volatility and suggest integrating risk management tools to stabilize the returns, which could make the strategy more viable for conservative investors. Employing DQN in terms of developing a trading strategy has shown its advantages in our recent works [115]. In that paper, we proposed a Multi-level DQN (MDQN) method that observes the daily closing price data of BTC along with Bitcoin-related tweets' sentiment data to suggest one of three main trading actions (buying, selling, and holding). The MDQN method, which consists of the Preprocessing-DQN and Main-DQN layers and a novel proposed reward function, was considered a significant contribution to the field, leading to a much enhanced trading strategy compared with other state-of-the-art methods. However, as the DQN algorithm struggles with large-scale action spaces, MDQN is designed to suggest the trading process only for single trading pairs, without specifying the optimal number of pairs to trade at any given time.

These studies collectively highlight the evolving nature of AI in cryptocurrency trading, demonstrating both the potential and challenges of leveraging AI to enhance trading strategies. Continuing with the exploration of AI in cryptocurrency trading, we delve into the practical applications and advancements of various machine learning models in enhancing trading strategies. The research done by Sattarov et al. [116] explores the effectiveness of DRL algorithms for recommending optimal trading points. They developed an application that leverages historical price data of BTC, ETH, and LTC to make real-time trading decisions. Their DRL approach resulted in notable profits, highlighting the potential of AI in navigating highly volatile markets. However, the authors recognize the need for improved risk management strategies to cope with the inherent unpredictability of cryptocurrency prices. Expanding on the theme of RL, Sihananto et al. [117] implemented RL algorithms to automate cryptocurrency trading, specifically noting that the A2C method yielded the best performance for low-volume trades with a reward of 0.332 in the BTC/USDT pair during testing phases. This adaptability of reinforcement learning algorithms, such as A2C and ACER—the latter being more effective for high-volume trades in ETH/USDT with a reward of 0.257—illustrates their potential to tailor strategies according to specific market conditions and trading volumes, enhancing overall trading profitability.

Research into algorithmic trading strategies for cryptocurrencies has shown promising advancements through the integration of AI techniques, notably machine learning and deep learning. Sumi et al. [118] leveraged both machine learning and deep learning to predict cryptocurrency prices, demonstrating that the Gated Recurrent Unit (GRU) model excelled with an R^2 score of 0.9983 for Ethereum, significantly higher than those achieved by linear regression models. This highlights the superior predictive power of GRU in capturing the complex dynamics of cryptocurrency markets, especially in terms of accuracy and reliability. Further exploring the effectiveness of different RNNs, Hamayel and Owda [119] compared GRU, LSTM, and bi-LSTM models, finding the GRU model to outperform others with the lowest mean absolute percentage error (MAPE) values for Litecoin at 0.2454%, for Bitcoin at 0.8267%, and for Ethereum at 0.2116%. These findings underscore GRU's enhanced capability to provide precise price forecasts, thus offering substantial benefits for traders seeking to optimize their entry and exit strategies in the volatile cryptocurrency markets.

Emphasizing the role of selecting algorithms and transaction fees in the cryptocurrency trading realm, Ahmad et al. [120] assessed the profitability of algorithmic trading strategies over short periods, revealing a varying performance among different algorithms. Specifically, reservation price algorithms yielded average returns of 7.5% over 15 days and 10% over 30 days, which were the highest among the tested strategies. In simulating trading strategies, Cocco et al. [121] utilized genetic algorithms to optimize trading rules within a simulated BTC/USD market. Their findings indicated that the best sets of trading rules, optimized through genetic algorithms, consistently outperformed others in both training and testing phases, suggesting that genetic algorithms can effectively identify and leverage profitable trading opportunities in a controlled setting. Similar results are reported by Patil [122]. He reviewed the broad application of AI in high-frequency trading, discussing how AI and genetic algorithms have been crucial in enhancing strategy

TABLE 4. Taxonomy of works studied trading strategy.

Models	Data Type	Methods
Technical Analysis	Historical price, trading data, stock data, market data, exchange data, number of total transactions, net profitability, profit percentage, technical indicators.	MACD with PSO [97], Genetic algorithm [98], MA and RSI [99], Optimal technical indicators [100], Gray model and ARIMA [101], EMA and RSI [102], MA and MACD [103], RSI and Bollinger bands [104], RSI and MACD [105], ETF and TTR [106], AHP-PSO [107], MACD-KURT strategy [108], SVM and linear regression [109], MACD, RSI with Fuzzy logic [110]
Algorithmic Trading	Open price, close price, volume, market price, trading data, Twitter sentiment data, crypto exchange data, high-frequency trading data, historical investment data.	ML algorithms [111], KNN [112], Duelling DQN [113], Deep Q-learning [114], M-DQN [115], DRL [116], A2C method [117], GRU model ([118], [119]), Set of trading algorithms [120], Genetic algorithms [121], AI and genetic algorithms [122], GRU model [123], PPO algorithm [124], LSTM ([125], [126])

optimization and risk management. The review elaborates on the transformative impact these technologies have on market prediction, which is essential for developing adaptive trading strategies that can respond to real-time market changes and maintain competitive advantages in fast-paced trading environments.

Continuing to explore AI-driven advancements in algorithmic trading for cryptocurrencies, recent studies delve into the integration of complex models, optimization techniques, and empirical analysis to further enhance the effectiveness and efficiency of trading strategies. These findings build upon previous research, offering new insights into machine learning applications, reinforcement learning advancements, and the dynamic adaptation of trading systems in response to market conditions. Zakhwan et al. [123] have significantly contributed to the field by employing LSTM, GRU, and Bi-LSTM models to forecast cryptocurrency prices. Their research revealed that GRU models, demonstrating superior accuracy with the lowest RMSE and MAPE, are particularly effective in navigating the complexities of cryptocurrency price movements. The study underscored GRU's effectiveness, noting RMSE values as low as 0.8076 and MAPE values of 0.2201, enhancing the reliability of predictions in trading scenarios. In parallel, Mahayana et al. [124] developed a model based on deep reinforcement learning using the Proximal Policy Optimization (PPO) algorithm. This model was trained to automate trading decisions on the cryptocurrency market, particularly focusing on optimizing trading points to maximize profitability. Their results showed that the model could outperform traditional buy-and-hold strategies, highlighting the practical implications of deploying deep reinforcement learning in real-time trading environments.

Further adding to the body of knowledge, Wan and Junze [125] demonstrated that using historical Bitcoin price data can be beneficial for developing trading strategies. Their model leveraged LSTM's capability to analyze historical price data, aiding investors in predicting future market trends. Additionally, they introduced a daily trading strategy model designed to guide daily capital management based on market dynamics. This approach is recognized for its simplicity, effectiveness, and adaptability to new datasets, making a significant contribution to quantitative investment strategies and cryptocurrency trading. Kavin [126] explored the utilization of machine learning in enhancing trading strategies and managing risks within the trading sector. The study provided comprehensive insights into how AI could be leveraged to predict stock market trends and optimize portfolio management. By implementing various machine learning models, the research offered practical solutions for risk assessment and strategy enhancement in trading operations, proving the substantial role of AI in improving financial outcomes in the stock market. To summarize the reviewed papers, Table 4 is given with the key studies focused on trading strategies, detailing the datasets, primary algorithms, and methods employed in each.

Collectively, these studies demonstrate a clear trajectory toward more sophisticated and effective use of AI in cryptocurrency trading. By leveraging deep learning and reinforcement learning models, researchers are able to enhance predictive accuracy. In addition to that, they also innovate in terms of trading strategy optimization and risk management, addressing some of the most pressing challenges faced by traders in the cryptocurrency markets. To gain a better understanding of the reviewed papers, we have selected a few from each model and described their pros and cons in Table 5.

C. EVALUATION METRICS

In this subsection, we will summarize the various evaluation metrics employed to assess the performance of trading strategies.

1) **Value at Risk (VaR).** Negative Value at Risk (VaR) is a metric used to assess the potential loss in value of a trading portfolio over a defined period for a given confidence interval. It helps in evaluating the risk associated with a trading strategy by estimating the maximum loss that could be incurred under normal market conditions [35]. The formal computation is given by:

$$\text{VaR} = \text{Quantile}_\alpha(P_t), \tag{7}$$

where $\text{Quantile}_\alpha(P_t)$ represents the α quantile of the portfolio's value distribution P_t at time t, and α is the confidence level (e.g., 95% or 99%).

2) **Expected Shortfall (ES).** This metric also known as Conditional Value at Risk (CVaR), is a risk measure

TABLE 5. Detailed summary of selected papers for Bitcoin trading strategies.

Model	Ref	Pros	Cons
Technical Analysis	Cohen [97]	The paper evaluates RSI, MACD, and Pivot Reversal trading strategies using particle swarm optimization.	The study's focus on Bitcoin limits the generalizability of the findings to other cryptocurrencies.
	Deac *et. al.* [98]	Paper effectively demonstrates the application of evolutionary algorithms for trading strategy optimization.	The focus on a specific trading strategy and a single stock (Nvidia) limits the applicability of the findings to other markets or assets.
	Bitto *et. al.* [99]	The paper provides a comprehensive analysis using historical price data and technical indicators like RSI.	The focus on historical data and traditional time series models may not capture sudden market changes and volatility effectively.
	Zishan *et. al.* [101]	Establishes a multiobjective dynamic programming model for optimal trading strategies, considering risk constraints like the Sharpe ratio.	The focus on gold and Bitcoin might restrict applicability to other assets with different volatility profiles.
	Song *et. al.* [107]	Combines AHP and PSO for optimizing investment ratios, showing improved returns with a strategy that balances risk and growth trends.	The complexity of integrating ARIMA, AHP, and PSO may limit accessibility.
	Lei *et. al.* [108]	Demonstrates significant improvements in total returns, Sharpe ratio, and risk management compared to the standard MACD approach.	The study is specific to CSI 300 index constituent stocks, potentially limiting applicability to other markets or assets.
	Rustam *et. al.* [110]	Combines MACD, RSI, Stochastic Oscillator, and On-Balance Volume indicators with fuzzy logic to enhance decision-making accuracy for buy, sell, or hold recommendations.	The study's focus on only two companies may restrict the generalizability of the findings to the broader Indonesian stock market.
Algorithmic Trading	Agarwal *et. al.* [111]	The Extra Trees Regressor demonstrates superior performance in terms of R^2 and MSE scores, providing robust predictions.	The paper highlights performance differences but may not fully explore the underlying reasons for these variations, limiting the depth of insights for further model improvements.
	Hawi *et. al.* [112]	Paper identifies KNN as the best overall performer, with SVM excelling for Bitcoin and LightGBM for Ethereum and Litecoin.	The study might not account for real-time market fluctuations and external economic factors, which could affect prediction accuracy in practical scenarios.
	Suliman *et. al.* [113]	The reinforcement learning approach adapts to market conditions, optimizing entry and exit points.	The Duelling DQN agent underperforms compared to the buy-and-hold strategy, highlighting areas for improvement in model robustness and efficiency.
	Sihananto *et. al.* [117]	The study shows that the Q-learning agent can effectively adapt to market conditions and optimize trading decisions, leading to significant returns.	The model's effectiveness is highly dependent on the quality of the reward function and the specific market conditions during the training period, which might limit its adaptability to different market environments.
	Sumi *et. al.* [118]	The GRU model demonstrates superior performance with high R^2 scores and minimal prediction errors, proving its robustness in price prediction tasks.	The reliance on historical price data may not fully capture real-time market fluctuations and external economic factors, potentially affecting the practical accuracy of the predictions.
	Ahmad *et. al.* [120]	The study provides a comprehensive comparison of different algorithms, revealing insights into the impact of transaction fees on trading profitability.	Focuses on short-term trading periods, which might not capture longer-term market trends and behaviors.
	Cocco *et. al.* [121]	The model effectively replicates real market behaviors, such as price series unit-root property, fat tail phenomenon, and volatility clustering, providing valuable insights into market dynamics and strategy optimization.	The model's reliance on genetic algorithms for strategy optimization may lead to overfitting, and the predefined trading rules might limit its adaptability to changing market conditions.
	Patil [122]	It demonstrates how AI techniques can enhance market prediction, risk management, and pattern recognition, showcasing the potential of AI-driven approaches in achieving real-time assessment and adaptive trading.	The paper focuses on theoretical and empirical analysis without extensive real-world testing, which could limit the direct applicability of the findings.
	Mahayana *et. al.* [124]	This paper highlights the potential of deep reinforcement learning in handling high-frequency trading data and complex decision-making processes.	Despite the innovative approach, the PPO model underperforms compared to the buy-and-hold strategy, indicating the need for further optimization and refinement.

used to assess the potential loss in value of a trading portfolio beyond the VaR threshold. It provides an estimate of the average loss given that the VaR threshold has been exceeded, offering a more comprehensive view of tail risk [36]. The formal computation is given by:

$$\mathrm{ES} = E[P_t \mid P_t \leq \mathrm{VaR}], \tag{8}$$

where $E[P_t \mid P_t \leq \mathrm{VaR}]$ represents the expected value of the portfolio's loss given that it does not exceeds the VaR threshold at time t.

3) **Sharpe Ratio (SR).** The metric used to evaluate the performance of a trading strategy by measuring the return per unit of risk. It is particularly useful in comparing the risk-adjusted performance of different portfolios or trading strategies [37]. The formal

TABLE 6. Summary of evaluation metrics used in this paper.

Class	Evaluation metrics	Equation
Price Prediction Metrics	MAE	$\frac{1}{n}\sum_{t=1}^{n}\lvert AP_t - PP_t\rvert$
	RMSE	$\sqrt{\frac{\sum_{t=1}^{n}(AP_t-PP_t)^2}{n}}$
	R^2	$R^2 = 1-(RSS/TSS)$ $RSS = \sum_{t=1}^{n}(AP_t - PP_t)^2$ $TSS = \sum_{t=1}^{n}(AP_t - \overline{AP})^2$
	MAPE	$\frac{1}{n}\sum_{t=1}^{n}\left\lvert\frac{AP_t-PP_t}{AP_t}\right\rvert \times 100\%$
	PPV	$\frac{TP}{TP+FP}$
	NPV	$\frac{TN}{TN+FN}$
Trading Strategy Metrics	VaR	$\text{Quantile}_{\alpha}(P_t)$
	ES	$E[P_t \mid P_t \leq \text{VaR}]$
	SR	$\frac{E[R_p-R_f]}{\sigma_p}$

computation is given by:

$$\text{SR} = \frac{E[R_p - R_f]}{\sigma_p}, \tag{9}$$

where $E[R_p - R_f]$ represents the expected excess return of the portfolio R_p over the risk-free rate R_f, and σ_p represents the standard deviation of the portfolio's excess return.

Table 6 provides a summary of the evaluation metrics used in this study, along with their respective equations. Once familiar with the foundational models and various approaches to price prediction and trading strategies, we can proceed to review other relevant studies. This exploration allows for assessing the breadth and depth of existing research, understanding the effectiveness of different models, and identifying gaps in the literature. By doing so, we aim to provide a comprehensive overview of how these predictive techniques have been applied and evolved in the context of cryptocurrency trading.

V. ROLE OF ACCURATE PRICE PREDICTION IN TRADING STRATEGY

In the dynamic world of financial markets, trading strategies are significantly influenced by the ability to forecast price movements accurately. This section delves into the pivotal role that accurate price prediction plays in shaping trading strategies, examining its impact through a comprehensive review of existing literature. We categorize the research findings into two distinct subsections: one highlighting the positive impacts of precise price forecasts on trading efficacy and decision-making, and another discussing the challenges and limitations posed by predictive models in trading contexts. By exploring these dimensions, this section aims to provide a balanced view of how price prediction influences strategic outcomes in trading, offering insights into both its potential benefits and its complexities.

A. POSITIVE IMPACTS OF ACCURATE PREDICTION ON TRADING STRATEGIES

Precise price prediction in the realm of cryptocurrency trading is considered crucial for enhancing trading strategies as it enables traders to anticipate market movements, optimize entry and exit points, and manage risks more effectively. By accurately forecasting future prices, traders can devise strategies that maximize returns while minimizing potential losses, making the accuracy of these predictions a pivotal factor in the success of trading activities.

Zhao et al. [127] developed a trading strategy using SVM based on technical indicators derived from historical data. Their models performed well in predicting price movements for cryptocurrencies like Bitcoin, Ethereum, and Litecoin. The study included a simulation of trading in a realistic environment, where their strategies outperformed the market by an average of 15%, demonstrating the practical application of their predictive models in live trading scenarios. Continuing on the practical application of predictive models, Zhao et al. [127] conducted a study on cryptocurrency price prediction and trading strategies using SVM. The research focused on predicting short-term price movements of major cryptocurrencies such as BTC, ETH, and LTC, and translating these predictions into profitable trading strategies. The SVM classifier, trained on a large set of technical indicators derived from historical price and volume data as well as on-chain data, predicted the next hour's price movement and informed trading decisions within a backtesting framework that simulated real market conditions. The empirical results showed that the SVM-based trading strategy consistently outperformed the market, achieving an average return of 20% with a 10% reduction in volatility. The classifier's accuracy in predicting profitable buy and sell opportunities was demonstrated by a PPV of 78% and a NPV of 75%.

Another instance where prediction outcomes were utilized to enhance a trading strategy is the study conducted by Li et al. [128]. They introduced a forecasting model that produces trading signals based on predicted Bitcoin market prices. Specifically, the model generates a buy signal if the predicted market price for the next day exceeds the current price, a sell signal if the predicted price is lower, and a hold signal if the predicted price remains unchanged. These signals guide algorithmic trading actions, resulting in an average return of 25%, outperforming several benchmark models and the buy-and-hold strategy by 10%. The robustness of the VMD-LMH-BiLSTM model was validated across multiple forecasting periods and testing intervals. Pillai et al. [129] presented a comprehensive system for cryptocurrency price prediction and trading, integrating machine learning and sentiment analysis to enhance trading strategies. The methodology employs LSTM for price prediction and VADER sentiment analysis to gauge market sentiment from news sources. The system's design includes a price prediction model, a sentiment analysis module, and a notification system. Empirical results demonstrated that the LSTM model achieved a high accuracy of 83% in predicting Bitcoin prices, while the sentiment analysis component provided additional context for price movements, leading to an increase in trading returns by 18%. This combination of elements ensured timely and informed trading actions, reducing risk by 12%. In a similar vein, Ji et al. [130] conducted a comparative study using different deep learning models, including DNN, LSTM, CNN, and deep residual networks (ResNet), for predicting Bitcoin prices and enhancing trading strategies. The authors developed both regression and classification models using Bitcoin blockchain information. The empirical results showed that LSTM-based models slightly outperformed others in regression tasks, achieving a MAPE of 5.2%, while DNN-based models excelled in classification tasks with an accuracy of 87%. Importantly, the study found that classification models were more effective for algorithmic trading, yielding higher profitability compared to regression models, with an average return increase of 22%. Ni and Yin [131] presented a hybrid neural network model aimed at improving exchange rate prediction to enhance trading strategies. The model integrates temporal self-organizing maps (TSOM) with SVR. TSOM clusters historical exchange rate data, capturing temporal dependencies, while SVR predicts future rates based on these clusters. The application of the TSOM-SVR model to real-world exchange rate data demonstrated significant improvements in predictive accuracy over traditional models, with an accuracy increase of 15%, which directly contributed to better trading outcomes and an average profitability increase of 18%. Lastly, Dolatsara et al. [132] developed an interpretable decision-support system for daily cryptocurrency trading. The authors used a tri-level feature selection approach, combining various market data indicators such as stock prices, crude oil prices, gold prices, and Wikipedia page views with Bitcoin price data to build a Classification and Regression Tree (C&RT) model. The model's high prediction accuracy of 97%, sensitivity of 95%, and specificity of 98% made it a reliable tool for predicting one-day-ahead Bitcoin price movements. The study also implemented a decision support tool based on the C&RT model, providing real-time trading signals that helped investors achieve an average return of 24%, even during periods of market volatility such as the COVID-19 pandemic.

The studies reviewed above collectively underscore the significant impact of accurate price prediction on enhancing cryptocurrency trading strategies. Across various methodologies—from SVM and deep learning models to hybrid neural networks and sentiment analysis—each approach demonstrated substantial improvements in trading outcomes. Notably, the empirical results revealed that integrating predictive models with trading strategies not only increased profitability but also reduced risk and market volatility.

B. CHALLENGES AND LIMITATIONS OF PRICE PREDICTION IN TRADING STRATEGIES

While the previous section highlighted the substantial benefits of integrating price prediction into trading strategies, it is equally important to recognize the challenges and limitations that can undermine these benefits. Real-life trading environments are inherently complex and unpredictable, often rendering even the most sophisticated predictive models less effective than anticipated.

One major challenge is the inherent volatility and rapid shifts in the cryptocurrency market. Even models with high predictive accuracy can fail to capture sudden market movements triggered by external factors such as regulatory changes, technological advancements, or macroeconomic events. For instance, Ciaian et al. [42] found that short- and long-run relationships between Bitcoin and altcoin markets can lead to unexpected price fluctuations, complicating the application of predictive models. Their study showed that shocks in Bitcoin prices had varying impacts on altcoins, leading to inconsistencies in prediction accuracy. Liu et al. [133] identified common risk factors in cryptocurrencies that contribute to their high volatility, making price predictions less reliable. They demonstrated that despite using sophisticated econometric models, the inherent risk factors led to substantial prediction errors, adversely affecting trading strategies. Makarov and Schoar [134] further demonstrated how trading and arbitrage activities in cryptocurrency markets can lead to price anomalies that prediction models struggle to capture. Their findings indicated that arbitrage opportunities caused by price discrepancies were quickly exploited, causing rapid market corrections that predictive models failed to anticipate. Urquhart [135] observed price clustering in Bitcoin, indicating that market participants' behaviors can cause deviations from predicted prices, leading to suboptimal trading decisions. His analysis revealed that psychological pricing points led to significant clustering, which predictive models did not account for, thus reducing their effectiveness in practical trading scenarios. In his work, Shintate and Pichl [136] developed a trend prediction classification framework for high-frequency Bitcoin time series using deep learning methods. They introduced the Random Sampling Method (RSM) to mitigate issues of non-stationarity and class imbalance in Bitcoin prices. Their results indicated that while RSM outperformed LSTM and MLP models in classification accuracy (with an F1 score of 0.5092 for BTCCNY and 0.5367 for BTCUSD), it did not outperform the buy-and-hold strategy in profitability, achieving lower returns compared to simple buy-and-hold during the testing period. This suggests that even sophisticated prediction models may not always translate into superior trading performance, especially in highly volatile markets.

Another limitation is the risk of overfitting, where models perform exceptionally well on historical data but fail to generalize to new, unseen data. This issue is particularly prevalent in machine learning and deep learning models, which may inadvertently learn noise or patterns that do not persist in real market conditions. Fischer and Krauss [137] highlighted this concern by showing that deep learning models like LSTM networks, while powerful, can overfit training data, reducing their effectiveness in live trading. They found that the LSTM model, despite achieving a high accuracy of 90% on historical data, performed poorly in real-time trading, achieving only a marginal 2% improvement over a random walk model. Gu et al. [138] emphasized the need for careful model validation to avoid overfitting in empirical asset pricing via machine learning. Their study showed that models trained with extensive cross-validation techniques performed better but still struggled with out-of-sample predictions, leading to inconsistent trading performance. Heaton et al. [139] discussed the challenges of deploying deep learning models in finance, noting that overfitting remains a significant barrier to their practical application. They highlighted that models showing high in-sample accuracy often failed to maintain performance in live trading due to overfitting to historical data patterns that did not repeat. Continuing in the same vein, Murray et al. [140] conducted a comprehensive comparison of machine learning, deep learning, and ensemble models for cryptocurrency price prediction. They evaluated models including ARIMA, k-NN, SVR, RF, LSTM, GRU, TCN, and TFT across multiple cryptocurrencies. Despite LSTM achieving the best predictive performance with an average RMSE of 0.0222 and MAE of 0.0173, their trading simulations revealed that these predictive models did not consistently lead to enhanced trading strategies. The authors noted that the high volatility and unpredictable nature of cryptocurrencies often led to discrepancies between predicted and actual prices, resulting in trading strategies that failed to outperform baseline approaches such as the buy-and-hold strategy.

Furthermore, many studies highlight the computational and data requirements necessary for effective model training and deployment. High-frequency trading strategies, for instance, require real-time data processing and rapid decision-making capabilities, which can be technically challenging and resource-intensive. Borovkova and Tsiamas [141] demonstrated that ensembles of LSTM networks require significant computational power to classify high-frequency stock market data accurately. They reported that their model, while achieving a high classification accuracy of 85%, required extensive computational resources, limiting its practicality for real-time trading. Krauss et al. [142] discussed the extensive data and computational needs for implementing deep neural networks and gradient-boosted trees in statistical arbitrage strategies on the S&P 500. Their study found that the high computational cost and data requirements of these models often outweighed the benefits, leading to only marginal improvements in trading performance.

Lastly, integrating predictive models into practical trading strategies involves navigating various operational and regulatory challenges. Ensuring model interpretability and compliance with financial regulations is crucial, especially for institutional traders. Barberis et al. [143] examined how extrapolation and bubbles in financial markets pose operational challenges for implementing predictive models. They found that models predicting price bubbles often failed to provide actionable insights due to their complexity and the unpredictable nature of bubbles. Fuster et al. [144] explored the impact of machine learning on credit markets, highlighting the predictably unequal outcomes that can arise without careful regulation. Their study showed that models, while improving credit predictions, often led to biased outcomes, necessitating stringent regulatory oversight. Gandal et al. [145] investigated price manipulation in the Bitcoin ecosystem, underscoring the regulatory challenges of maintaining market integrity while employing advanced predictive models. Their findings revealed that manipulative practices significantly distorted market prices, making it difficult for predictive models to provide reliable trading signals.

In light of these challenges, this subsection reviews several studies that, despite achieving good price prediction results, reported disappointing performance in their trading strategies. These studies highlight the nuanced and multifaceted nature of applying predictive models to real-world trading and underscore the need for ongoing research and development to address these limitations.

VI. FUTURE TRENDS AND INNOVATIONS

As the cryptocurrency market evolves, emerging technologies in machine learning and data analytics are set to revolutionize trading strategies and price forecasting techniques. These innovations are driven by the need for more accurate and adaptive models that can handle the complexity and volatility of cryptocurrency markets. By leveraging advanced algorithms and integrating diverse data sources, these technologies are poised to provide traders with significant advantages. This section explores the potential impact of these innovations and considers the implications of global regulatory changes on cryptocurrency trading and prediction strategies.

A. ADVANCED MACHINE LEARNING TECHNIQUES

The use of RNN and their variants, such as LSTM and GRU, is increasingly seen as a promising trend in cryptocurrency price prediction due to their ability to capture temporal dependencies in data. Seabe et al. [146] demonstrated that Bi-Directional LSTM outperformed both LSTM and GRU in predicting BTC, ETH, and LTC prices, achieving low MAPE values of 0.036 for BTC, 0.124 for ETH, and 0.041 for LTC. This high level of accuracy underscores the potential of Bi-LSTM in capturing the intricate patterns in cryptocurrency price movements. Another study by Khan et al. [147]

confirmed the effectiveness of GRU models, showing they achieved an RMSE of 366.0601 and a MAPE of 1.7268% for BTC, indicating robust performance in price prediction.

DRL represents another future trend due to its capability to develop automated trading strategies that can adapt to changing market conditions. For instance, Kong and So [148] developed an ensemble strategy combining multiple actor-critic algorithms, including A2C, DDPG, PPO, and notably TD3, to improve automated stock trading. Their research demonstrated that incorporating TD3 in the ensemble led to a more robust trading agent capable of achieving cumulative returns higher than traditional methods. The TD3 algorithm, in particular, contributed to more stable and significant returns, validating its effectiveness in diverse market conditions. Further, Kabbani and Duman [149] employed the TD3 algorithm within a DRL framework to automate stock trading. Their model addressed the dual challenges of prediction and portfolio allocation, achieving a Sharpe Ratio of 2.68 on unseen test data. This robust performance underscores the TD3 algorithm's capability to enhance trading strategies by balancing risk and return effectively in real-world trading environments.

Moreover, Taghian et al. [150] developed a novel DRL model that utilized multiple feature extraction modules to generate asset-specific trading signals. By applying this model to different assets, including cryptocurrencies, they achieved a total return of nearly 262% over two years, significantly outperforming other state-of-the-art models. This study emphasizes the importance of tailored trading strategies to maximize returns and minimize risks in the volatile cryptocurrency market. Finally, Yu [151] explored quantitative trading using the TD3 algorithm and demonstrated its superior performance compared to traditional moving average strategies. The annualized return rate of the TD3 algorithm was between 23% and 25%, significantly higher than the 10% to 15% achieved by the moving average strategy over the past decade. This highlights the TD3 algorithm's potential to provide actionable insights and improve investment returns for both individual and institutional investors.

Integrating machine learning with NLP for sentiment analysis has shown significant promise in enhancing cryptocurrency price predictions. Gurgul et al. [152] employed advanced deep learning NLP methods to analyze social media data from platforms like Twitter and Reddit, discovering that incorporating NLP data significantly improved the forecasting performance of their models. Their findings revealed that pre-trained models such as Twitter-RoBERTa and BART MNLI were particularly effective in capturing market sentiment, which is crucial for making accurate price predictions. Similarly, Murugesapandian [153] demonstrated the efficacy of an LSTM-GRU ensemble model in performing sentiment analysis and emotion detection on Bitcoin-related tweets, achieving high accuracy scores of 0.91 for sentiment analysis and 0.83 for emotion detection. Hybrid machine learning models, which combine multiple algorithms to enhance prediction accuracy, are also gaining traction. Nair et al. [154] proposed a hybrid approach using RNN, LSTM, GRU, Bi-LSTM, and 1D convolutional neural networks (CONV1D) for predicting Bitcoin prices. Their study found that LSTM outperformed the other models, with an RMSE of 1978.68268 and an R-squared score of 0.94383, indicating its superior performance in capturing complex market dynamics.

B. IMPACT OF GLOBAL REGULATORY CHANGES

The evolving landscape of global regulations poses significant challenges and opportunities for cryptocurrency trading and prediction strategies. Regulatory changes can influence market behavior, trading volumes, and overall market stability. Understanding and adapting to these changes is crucial for traders and investors. Examining the integration of macroeconomic and microeconomic theories with machine learning approaches, Erfanian et al. [155] highlighted the significance of technical indicators and macroeconomic factors in long-term price prediction. Their findings underscore the need to consider regulatory impacts on cryptocurrency markets. Building on this, Karahan and Ögüdücü [156] developed a heuristic-guided reinforcement learning approach for automated cryptocurrency trading, demonstrating its potential to navigate regulatory changes and market volatility. This approach underscores the adaptability required for effective trading strategies in the face of regulatory shifts. Additionally, Dinshaw et al. [157] examined the prediction capability of different time series machine learning models, including LSTM, ARIMA, and SARIMA, in forecasting Bitcoin prices. Their findings indicated that LSTM models performed best, suggesting their robustness under varying regulatory environments. Complementing this, Puri et al. [158] explored the application of SVM and Random Forest algorithms in predicting cryptocurrency prices, emphasizing the importance of adapting to regulatory impacts to improve trading strategies. Further emphasizing adaptability, Mariappan et al. [159] proposed a reinforcement learning-based approach integrated with a blockchain framework for secure and efficient price forecasting. Their model showed improved consistency and accuracy in predicting prices for cryptocurrencies like BTC and LTC, highlighting the importance of secure and adaptive models in a changing regulatory landscape.

As the integration of advanced machine learning and data analytics techniques continues to shape the future of cryptocurrency trading, the potential for these technologies to revolutionize trading strategies and price forecasting remains immense. By leveraging the capabilities of RNN variants, DRL algorithms, and hybrid models, traders and investors are better equipped to navigate the complexities and volatilities of the cryptocurrency market. Additionally, the incorporation of NLP for sentiment analysis and the adaptation to global regulatory changes further enhance the robustness and effectiveness of these strategies.

C. CHALLENGES AND FUTURE DIRECTIONS

While the advancements in machine learning and data analytics have significantly enhanced cryptocurrency trading strategies and price forecasting techniques, several challenges and opportunities for future research remain. Below, we outline key challenges and suggest directions for future work:

- **Regulatory Uncertainty:** The ever-evolving regulatory landscape poses a significant challenge to cryptocurrency trading. Regulatory changes can impact market behavior, trading volumes, and overall market stability. Traders and investors must continuously adapt to new regulations, which can vary widely across different jurisdictions [156]. Addressing this challenge requires the development of adaptive models that can dynamically adjust to new regulatory changes. Incorporating regulatory data as part of the model inputs can help in forecasting regulatory impacts on market behavior.
- **Market Volatility:** Cryptocurrency markets are highly volatile, which makes accurate price prediction and risk management challenging. Sudden market movements and the influence of external factors (e.g., geopolitical events, and technological advancements) can lead to unpredictable market behaviors [148]. To manage and predict market volatility more effectively, robust algorithms need to be developed. Future work should explore adaptive and real-time models capable of adjusting to sudden market changes and external shocks, enhancing risk management and prediction accuracy.
- **Data Quality and Integration:** The integration of diverse data sources, such as social media sentiment and macroeconomic indicators, requires sophisticated models capable of processing and analyzing vast amounts of information in real time. Ensuring the quality and reliability of data is crucial for accurate predictions, yet challenging due to the dynamic and unstructured nature of some data sources [152]. Future research should focus on advanced data integration methods to handle vast and diverse sources of data effectively. Employing sophisticated data validation and cleansing methods can improve data quality, ensuring more accurate and reliable predictions.
- **Model Interpretability:** The complexity of advanced machine learning models often leads to a trade-off between accuracy and interpretability. It is essential to develop models that not only provide accurate predictions but also offer insights that are understandable and actionable for traders and investors [153]. To address this, there is a growing need for explainable AI (XAI) techniques. Research in this area can help make complex models more transparent and interpretable, allowing traders to understand and trust the predictions while maintaining high accuracy. Another possible solution is developing hybrid and ensemble models that can enhance prediction accuracy and robustness. These approaches combine multiple algorithms to leverage their strengths and provide more reliable and stable predictions.

While significant progress has been made in the field of cryptocurrency trading and price prediction, addressing these challenges and pursuing these future directions will be important for advancing the field. By leveraging cutting-edge technologies and adopting adaptive, regulation-aware strategies, traders and investors can enhance their trading performance and contribute to the development of more resilient and efficient financial markets.

VII. CONCLUSION

In this review, we explored the landscape of cryptocurrency trading strategies and price forecasting techniques. The volatility of cryptocurrency markets necessitates advanced predictive models and sophisticated trading strategies. We examined various predictive models, including economic theories, statistical methods, machine learning techniques, and sentiment analysis. Each model brings unique strengths, with economic models focusing on supply and demand principles and machine learning capturing complex data relationships. Sentiment analysis adds value by incorporating real-time market sentiment.

Our review highlighted the importance of technical analysis and algorithmic trading. Technical analysis, using historical data, remains crucial, with optimized indicators like moving averages, RSI, and MACD improving outcomes. Algorithmic trading, driven by AI and machine learning, represents the future, automating complex decisions and adapting to real-time conditions. Accurate price predictions are critical for effective trading strategies, helping traders optimize entry and exit points and manage risks. However, the market's inherent volatility requires continuous improvement in models and strategies. Future trends point to advanced machine learning techniques (RNN, LSTM, GRU, DRL) playing a key role. Integrating diverse data sources, including social media sentiment and macroeconomic indicators, will enhance predictive power. Adapting to evolving regulatory landscapes will also be essential.

In conclusion, the intersection of accurate price prediction and sophisticated trading strategies offers a promising path for traders and investors. Leveraging advanced technologies and staying informed about emerging trends will help navigate market complexities and contribute to resilient financial systems. Future research should explore hybrid models, interdisciplinary approaches, and ethical considerations to advance the field and ensure sustainable growth of cryptocurrency markets.

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