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Deep Temporal Convolutional Networks for High Frequency Cryptocurrency Price Forecasting

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Abstract. This survey reviews the application of Deep Temporal Convolutional Networks (TCNs) in high-frequency cryptocurrency price forecasting, a field challenged by extreme volatility and non-stationary dynamics. Recent studies demonstrate that TCNs achieve superior performance over traditional machine learning models and recurrent architectures by efficiently capturing long-range temporal dependencies through parallelizable structures. We synthesize findings across different market regimes, highlighting TCNs' advantages in computational efficiency, robustness, and adaptability to rapidly shifting trading environments. Moreover, the review examines emerging efforts to enhance interpretability, addressing a key barrier to real-world adoption in financial systems. By consolidating current progress and open challenges, this paper underscores the significance of TCNs as a promising direction for building more reliable forecasting frameworks, while outlining future opportunities to strengthen their practical impact in algorithmic trading and financial decision-making.

Keywords: Cryptocurrency forecasting, High-frequency trading, Temporal Convolutional Networks (TCNs), Financial time series, Long-range dependencies, Algorithmic trading

1. Introduction

Short-horizon cryptocurrency forecasting sits at the intersection of market microstructure research, non-stationary time-series analysis and scalable deep learning. Unlike traditional asset classes, crypto markets operate continuously and cycle through abrupt trend reversals, volatility spikes and long consolidation phases. These properties complicate validation and model selection because headline accuracy often reflects the prevailing regime more than any stationary law [1]. Prior work spans gradient-boosted trees, ensemble methods and support vector machines, alongside recurrent architectures such as LSTMs. Classical models are prized for transparency and fast inference but tend to underfit nonlinear temporal dependencies present in order-book and tick data; deep sequence models capture such dependencies at the cost of heavier optimization and reduced interpretability in production settings [2].

Within deep sequence modeling, Temporal Convolutional Networks (TCNs) have emerged as a pragmatic alternative to recurrent networks. By combining causal structure with dilated convolutions, TCNs obtain large receptive fields without recursion, learning long-range temporal dependencies while mitigating vanishing gradients and enabling fully parallel training [3]. These

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traits matter operationally in digital-asset markets: microstructure signals are multi-scale, trading is 24/7, and live pipelines must trade off predictive lift against throughput, latency and retrain frequency [1, 2]. As a result, TCNs increasingly serve as the backbone in short-horizon crypto forecasting systems, particularly when inputs combine depth-of-book, trade flow and realized-volatility proxies in multi-channel tensors [3].

Therefore, this paper reviews the use of Temporal Convolutional Networks (TCNs) for high-frequency cryptocurrency price forecasting, evaluating their potential, performance, and interpretability compared to traditional machine learning models and recurrent neural networks in capturing market nonlinearity and temporal dependencies. Beyond its technical contribution, the study is intended to provide a clear entry point for readers who wish to become familiar with these emerging methods. In particular, we aim to outline the mathematical foundations of sequence modeling in this domain, highlight recent methodological advances in convolution-based temporal learning, and discuss their practical relevance in financial signal analysis and short-horizon prediction tasks.

2. Literature review

The evolution of forecasting models for cryptocurrency markets has progressed through several distinct phases, reflecting both technological advancements and growing understanding of market dynamics. Initial research efforts focused on adapting classical econometric methods to digital assets, with techniques such as ARIMA and GARCH modeling representing the first systematic approach to price prediction. These methods provided a mathematical foundation for understanding market behavior but ultimately proved inadequate for capturing the extreme volatility and nonlinear patterns characteristic of cryptocurrency markets. This limitation became particularly evident during periods of sudden market shifts, where traditional models consistently failed to provide accurate forecasts [4]. The recognition of these limitations prompted a shift toward machine learning approaches, marking the second phase in the development of forecasting methodologies. Researchers began employing support vector machines, random forests, and various ensemble methods that could capture nonlinear relationships in market data. These models demonstrated improved performance by incorporating diverse features such as historical price patterns, trading volumes, and market sentiment indicators [1]. The adaptability of these methods to different market conditions and their relative computational efficiency contributed to their widespread adoption. However, they still struggled with capturing temporal dependencies and required substantial feature engineering, which limited their effectiveness in high-frequency trading scenarios [5]. The most recent phase in this evolutionary process has been characterized by the adoption of deep learning architectures specifically designed for sequential data processing. The emergence of recurrent neural networks, particularly long short-term memory networks and gated recurrent units, represented a significant advancement in handling time-dependent patterns in financial data [2]. These developments eventually led to more specialized architectures including temporal convolutional networks and attention-based mechanisms, which offered improved computational efficiency and better handling of long-range dependencies in time series data [3, 6].

2.1. First stage models: traditional machine learning

Traditional machine learning methods laid the groundwork for contemporary cryptocurrency forecasting by advancing beyond elementary statistical models. These approaches enabled the detection of intricate nonlinear relationships in market data that conventional econometric

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techniques could not reveal. Tree-based algorithms, especially random forests and gradient boosting machines, became particularly popular in cryptocurrency prediction due to their consistent performance amid changing market conditions [7, 8]. A key feature of these models is their ability to measure feature importance, allowing analysts to determine which factors most significantly influence price movements. From a practical perspective, these methods provided clear advantages. Their relatively low computational requirements made them accessible to researchers with limited resources, and their interpretability helped clarify fundamental market mechanisms. The capacity to trace predictions back to specific variables rendered these approaches particularly useful for exploratory research and for creating baseline models [8]. They also demonstrated resilience in data-scarce environments, frequently producing usable outcomes without the massive datasets typically needed for deep neural networks. Nevertheless, these conventional machine learning techniques revealed important weaknesses in cryptocurrency forecasting. A primary drawback was their inherent inability to model temporal dependencies, since they process inputs as independent observations rather than as parts of a sequential flow. This shortcoming compelled researchers to devote considerable effort to manual feature engineering aimed at incorporating temporal information—attempts that often fell short of capturing the complex, evolving nature of cryptocurrency markets [9]. Additionally, the comparatively rigid structure of these models reduced their flexibility during sudden volatility surges, when market dynamics can shift rapidly [4].

2.2. Second stage models: recurrent deep learning

The introduction of recurrent neural networks marked a substantial advancement in cryptocurrency forecasting capabilities. These architectures addressed fundamental limitations of previous approaches by explicitly designed to handle sequential data through their internal memory mechanisms. Long short-term memory networks and related variants demonstrated remarkable effectiveness in capturing temporal patterns that persisted over varying time horizons, making them particularly suitable for financial time series analysis [2, 10]. This capability proved especially valuable in cryptocurrency markets, where price movements often exhibited momentum effects and volatility clustering that extended across multiple time scales. Recurrent models offered several distinct advantages over traditional machine learning approaches. Their ability to automatically learn relevant temporal patterns from raw data eliminated the need for manual feature engineering regarding time dependencies. Furthermore, these architectures demonstrated superior performance in adapting to non-stationary market conditions, maintaining predictive accuracy during both stable periods and phases of high volatility [10]. The flexibility of these models allowed them to capture complex nonlinear relationships that evolved over time, providing a more comprehensive representation of market dynamics than was possible with previous approaches. However, the implementation of recurrent architectures also introduced new challenges that limited their practical application. The sequential nature of these models resulted in significant computational requirements, particularly when processing high-frequency data streams over extended time periods [11]. Training these networks often proved difficult due to issues with vanishing gradients, which could impede the learning of long-term dependencies. Additionally, the black-box nature of these models complicated interpretation of their decision-making processes, making it difficult to understand the specific factors driving their predictions [12]. These limitations motivated the development of alternative architectures that could preserve the temporal modeling capabilities while addressing these practical concerns.

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2.3. Third stage models: convolutional and attention-based approaches

Contemporary research in cryptocurrency forecasting has increasingly focused on convolutional and attention-based architectures that address limitations of recurrent models. Temporal convolutional networks utilize dilated causal convolutions to achieve expansive receptive fields while maintaining computational efficiency through parallel processing capabilities [3]. This architectural approach enables effective modeling of long-range dependencies without encountering the gradient instability problems that often affect recurrent networks. The design principles underlying these models were influenced by earlier work in sequence generation tasks, which demonstrated the effectiveness of dilated convolutions for capturing multi-scale patterns [13]. The practical application of these advanced architectures has demonstrated significant improvements in forecasting performance. Studies investigating convolutional approaches for time series forecasting have shown their ability to effectively capture both short-term volatility patterns and longer-term market trends [14]. In cryptocurrency markets specifically, these models have proven particularly valuable for high-frequency forecasting scenarios where both computational efficiency and accuracy are critical requirements [6]. The parallelizable nature of these architectures provides substantial advantages in practical deployment situations, where reduced training times can significantly impact model utility.Attention mechanisms have further enhanced forecasting capabilities by enabling models to dynamically focus on the most relevant portions of input sequences. The integration of attention with convolutional and recurrent components has produced architectures that offer improved interpretability alongside high predictive accuracy [6, 15]. These hybrid approaches allow for identification of which historical time points most significantly influence predictions, providing valuable insights into model behavior. This transparency represents a significant advancement for financial applications, where understanding model decisions is often as important as predictive accuracy itself [15]. Despite these advancements, current state-of-the-art approaches continue to face important challenges that require further research. The performance of convolutional and attention-based models remains sensitive to hyperparameter configurations and architectural details, necessitating careful optimization for specific market conditions [12]. Additionally, these models may still struggle with exceptionally volatile or non-stationary market regimes that deviate significantly from patterns observed in training data. The complexity of these architectures also complicates implementation and deployment in practical trading environments, where computational constraints and latency requirements may impose additional limitations [9].

3. Application

3.1. Algorithmic trading and strategic execution

In the realm of cryptocurrency markets, advanced forecasting models have become fundamental components of algorithmic trading systems. These systems leverage the capabilities of temporal convolutional networks and long short-term memory models to process high-frequency sequential data with minimal latency, enabling automated trading platforms to exploit minute price discrepancies across global exchanges [6]. Modern trading algorithms incorporate these models to analyze real-time order book dynamics, historical trade sequences, and short-term volatility patterns, generating predictions over extremely short time horizons ranging from milliseconds to minutes. The practical implementation of these systems allows trading firms to execute complex strategies that would be impossible for human traders, including market making, arbitrage, and momentum trading [10]. Beyond mere price prediction, these models are increasingly integrated into risk

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management frameworks where they monitor for abnormal trading patterns or sudden liquidity shifts that may indicate market manipulation or emerging systemic risks [15]. By connecting model predictions with predefined risk parameters, trading platforms can automatically initiate protective measures such as position adjustments or temporary trading halts, thereby reducing potential losses during periods of extreme market volatility.

3.2. Risk management and portfolio optimization

The application of forecasting models extends significantly into risk control and investment portfolio management. Given the notorious volatility of cryptocurrency markets, institutional investors and fund managers utilize predictive models to identify potential risk scenarios and optimize asset allocation strategies [4]. Sophisticated forecasting systems provide early warnings of possible trend reversals or volatility expansions, enabling portfolio managers to adjust their holdings, increase hedging activities, or reallocate assets into more stable instruments [5]. The integration of these models with traditional portfolio theory has facilitated more sophisticated cryptocurrency investment strategies that balance return objectives with risk constraints. For instance, predictive models that estimate value-at-risk or expected shortfall have become valuable tools for determining position sizes and setting stop-loss levels [9]. Furthermore, these forecasting capabilities support the ongoing process of portfolio rebalancing, allowing investors to maintain their desired risk exposure despite the rapidly changing market conditions characteristic of digital asset markets [12].

3.3. Market surveillance and regulatory technology

Beyond their applications in trading and investment, forecasting models have also become indispensable for enhancing market oversight and regulatory compliance. Exchanges and regulatory bodies increasingly utilize these tools to flag suspicious trading activities, identify manipulative practices---such as wash trading or spoofing---and detect operational anomalies that could compromise market integrity [15]. By probing into order book dynamics, transaction histories, and cross-exchange price linkages, these systems help uncover potentially manipulative behaviors that might otherwise escape detection [14]. Such monitoring capabilities are especially critical in cryptocurrency markets, where regulatory frameworks remain in development and the potential for market abuse is elevated. Moreover, forecasting models enable exchanges to project liquidity requirements and respond proactively during periods of market stress, thereby promoting greater stability [11]. Regulatory technology applications continue to develop as authorities seek to understand and monitor these complex markets, with predictive models providing valuable insights for policy development and enforcement actions [6]. This application domain demonstrates how forecasting technologies contribute not only to private profit but also to the development of more transparent and trustworthy digital asset markets.

4. Discussion & conclusion

Even though TCNs have shown strong results, they still face some challenges in practice. One main issue is the unstable nature of cryptocurrency markets. A model trained on past data may perform poorly when sudden events occur, such as new regulations, global news, or large shifts in investor sentiment [1]. Although TCNs can capture longer sequences better than many recurrent models, their success still depends on the quality and range of the training data [3]. Another limitation is

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interpretability. While tools like SHAP or attention-based methods improve understanding of model decisions [15], many people in finance still see deep learning systems as "black boxes." Furthermore, training TCNs requires large datasets and high computing power, which may not be practical for smaller firms or independent traders compared to lighter models such as gradient boosting or CNN-based approaches [2, 14]. Despite these limits, evidence suggests that TCNs are a promising alternative to existing methods. Their ability to capture both short- and long-term dependencies makes them especially useful in high-frequency trading. Future research could look at hybrid systems that combine TCNs with other approaches such as Temporal Fusion Transformers (TFTs) [6], or include extra data, such as blockchain activity or market news, to make predictions more robust. In conclusion, TCNs are not a complete solution, but they represent an important step forward in forecasting cryptocurrency prices. Their use in trading strategies, risk management, and financial platforms shows their wide potential. With further progress in efficiency and transparency, TCNs are likely to become a key tool in the future of digital finance.

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