*Research Paper*
*Computational Methods for Differential Equations*
http://cmde.tabrizu.ac.ir
Vol. *, No. *, *, pp. 1-9
DOI:10.22034/cmde.2025.69796.3445

# Fuzzy growing map for analyzing cryptocurrency market trends

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**Abstract**

The cryptocurrency market is renowned for its rapid fluctuations and high volatility, making trend prediction a significant challenge due to the complexity and noise in the data. Traditional predictive models often struggle with such unstructured and high-dimensional datasets. This study introduces the **Fuzzy Growing Map (FGM)** as a cutting-edge approach to analyze cryptocurrency market trends. FGM combines fuzzy logic with dynamic growing maps to uncover hidden patterns and correlations in the data, making it especially suitable for the unpredictable and fast-paced nature of the cryptocurrency domain.

What sets FGM apart from conventional methods like neural networks, support vector machines, and regression models is its ability to **dynamically adjust to new market changes in real-time**, without the need for time-consuming retraining. Unlike static models, FGM autonomously identifies key features from the input data and adapts continuously to emerging market conditions. When tested on historical cryptocurrency data, FGM demonstrated an impressive **92.3%** predictive accuracy, **surpassing traditional models by 8-12%**.

The results reveal that FGM is not only more adaptive and responsive to market shifts but also more efficient in predicting trends, offering a significant improvement over existing methods. This makes FGM a groundbreaking tool for the future of cryptocurrency market forecasting, capable of tackling the challenges posed by the volatility and noise inherent in these markets.

**Keywords.** Fuzzy growing map (FGM), Cryptocurrency market prediction, Machine learning, Trend forecasting, Real-time adaptation.

**2010 Mathematics Subject Classification.** 68T10, 03E72,62H30, 68T014.



## 1. Introduction

The cryptocurrency market, encompassing assets like Bitcoin, Ethereum, and various altcoins, has seen explosive growth and volatility in recent years. Unlike traditional financial markets, where asset prices often follow patterns influenced by established economic indicators, cryptocurrency prices are driven by an intricate combination of factors such as technological innovations, market sentiment, and regulatory changes. This complexity, coupled with high market volatility, makes accurate price prediction particularly challenging, especially for short-term forecasting and high-frequency trading applications. Consequently, there is a growing need for advanced computational models capable of navigating the noisy, high-dimensional, and often ambiguous data environments characteristic of cryptocurrency markets.

Traditional machine learning models, such as time series analysis, regression models, and Support Vector Machines (SVM), have been widely used for financial forecasting. However, these methods often struggle to capture the complex, non-linear relationships that define cryptocurrency price movements. The inherent volatility and irregular nature of cryptocurrency data pose significant challenges for conventional techniques, which typically require extensive retraining when market conditions change, leading to inefficiencies and delayed responses [2, 8]. These limitations underscore

Received: 21 October 2025; Accepted: 11 November 2025.
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the need for more adaptive and robust models that can process uncertainty and adjust to rapidly changing data in real time.

The **Fuzzy Growing Map (FGM)** algorithm [12] presents a promising solution to these challenges. FGM is a non-linear, adaptive machine learning technique that integrates **fuzzy logic** with a **dynamic growing map structure**. This hybrid approach allows FGM to autonomously identify and adapt to the most influential features of input data, making it highly effective for the volatile cryptocurrency market. Fuzzy logic empowers the model to handle the inherent uncertainty and imprecision found in cryptocurrency data, while the growing map structure allows FGM to continuously evolve as new data arrives. Unlike traditional models, which often require complete retraining to adjust to shifting market conditions, FGM's ability to dynamically adapt to new data makes it exceptionally well-suited for real-time applications such as cryptocurrency trend prediction.

Furthermore, a growing body of literature has focused on hybrid approaches that combine fuzzy logic with other advanced techniques, such as deep learning and ensemble methods, to enhance prediction accuracy in volatile markets. Recent work has explored the potential of integrating FGM with Deep Neural Networks (DNN) and Reinforcement Learning (RL) for improved decision-making in high-stakes environments like cryptocurrency trading [7, 8]. These hybrid models aim to leverage the strengths of multiple techniques, ensuring higher resilience to noise and market shifts, thus enhancing predictive reliability.

In this study, we investigate the application of FGM for predicting cryptocurrency market trends and compare its performance with other popular machine learning models, including Artificial Neural Networks (ANN), Support Vector Machines (SVM), and traditional regression models. Our experimental results demonstrate that FGM significantly outperforms these models, achieving a predictive accuracy of $\mathbf{92.3}\%$, which is approximately $\mathbf{8-12}\%$ higher than the best-performing conventional models. These findings suggest that FGM is a superior tool for forecasting cryptocurrency market trends, offering substantial advantages in real-time prediction and resilience to volatility.

The remainder of this paper is structured as follows: Section 2 introduces the FGM algorithm and its application to cryptocurrency market prediction. Section 3 provides a comprehensive overview of the experimental evaluation, including details on the dataset, preprocessing steps, evaluation metrics, and comparative analysis with state-of-the-art models. Section 4 delves into the implementation and optimization details of the FGM. Section 5 discusses the adaptivity and real-time performance of FGM. Finally, section 6 provides concluding remarks and suggestions for future research.

## 2. Methodology

In this section, we present the detailed methodology of the Fuzzy Growing Map (FGM) algorithm for analyzing cryptocurrency market trends. FGM is a powerful tool that combines fuzzy logic with a growing map structure, which allows it to handle the volatility and uncertainty inherent in financial data, particularly in the cryptocurrency markets. The following subsections will discuss the fundamental principles, the mathematical formulation, and the steps involved in the implementation of the FGM algorithm.

### 2.1. The Fuzzy Growing Map (FGM) Algorithm.

The FGM algorithm is designed to model and predict trends in dynamic and noisy data environments such as cryptocurrency markets. It integrates fuzzy logic with a growing map architecture, which allows the model to adapt to new information in real time without requiring full retraining. The algorithm is composed of two primary components: fuzzy logic for handling uncertainty and the growing map for dynamic adaptation to incoming data.

2.1.1. *Fuzzy Logic in FGM.* Fuzzy logic is used in FGM to manage **uncertainty and imprecision** in the data. Traditional models struggle to work with noisy and incomplete data, which is typical in financial markets. The fuzzy system assigns a degree of membership to each data point, allowing it to express the degree of certainty with which an input belongs to a particular class. This helps in capturing the nuanced relationships in the market data. The fuzzy membership function for each input feature $x_i$ is defined using a sigmoid function:

$$\mu_i(x_i) = \frac{1}{1 + e^{-\alpha_i (x_i - \beta_i)}},$$

where:

- $\mu_i(x_i)$ represents the membership value of the input feature $x_i$,
- $\alpha_i$ controls the steepness of the curve (fuzzification factor),
- $\beta_i$ is the center of the membership function.

The fuzzy logic system thus transforms the raw input data into fuzzy values, which are more suitable for prediction and analysis, especially in noisy environments.

2.1.2. *Growing Map for Real-Time Adaptation.* The growing map component is central to the FGM algorithm. It enables the system to **dynamically adapt** to new data, which is crucial in the fast-moving cryptocurrency market. Unlike static models, the growing map expands over time, adding new nodes and adjusting the connections between them as new data is processed. This allows the model to capture emerging patterns and trends that may not have been apparent at the time of initial training.

Mathematically, the weight vector $\mathbf{W}$ of the winning node (Best Matching Unit, BMU) in the growing map is updated in an online fashion based on the incoming data:

$$\mathbf{W}_{i+1} = \mathbf{W}_i + \eta(t) \cdot (\mathbf{x}_i - \mathbf{W}_i),$$

where

- $\mathbf{W}_i$ is the weight vector of the BMU at time step $i$,
- $\mathbf{x}_i$ is the current input vector,
- $\eta(t)$ is the time-dependent learning rate, controlling how quickly the map adapts.

The growing map adjusts its structure as new data points arrive, ensuring that the model remains relevant and accurately reflects the latest market conditions. The growth mechanism involves inserting a new node between the BMU and its most frequently activated neighbor if the error (distance) of the BMU exceeds a predefined threshold.

2.2. **FGM Workflow.** The FGM algorithm follows a systematic workflow for processing and predicting cryptocurrency market trends:

(1) **Data Preprocessing**: Raw cryptocurrency market data is collected, which includes historical price movements, trading volumes, and other relevant features. Preprocessing steps include normalizing the data and handling any missing values.
(2) **Fuzzy Membership Calculation**: Each feature in the dataset is processed using the fuzzy membership functions to calculate its degree of membership. This step transforms the data into fuzzy values that capture the inherent uncertainty in the market.
(3) **Growing Map Initialization and Expansion**: The growing map initializes with a small number of nodes. As new data is processed, the map dynamically expands by adding new nodes and adjusting existing connections to better capture emerging market trends.
(4) **Trend Prediction**: After training, the FGM model is used to predict future cryptocurrency market trends. The model evaluates the current market data and computes the most likely future trends based on the patterns learned from the growing map.

2.3. **Advantages of FGM Over Traditional Models.** The FGM algorithm offers several advantages over traditional machine learning models, such as Artificial Neural Networks (ANNs), Support Vector Machines (SVMs), and regression models, which are commonly used for cryptocurrency market prediction.

- **Adaptivity**: FGM's growing map structure allows it to adapt in real time as new data arrives, making it highly suitable for the fast-moving and volatile cryptocurrency market. In contrast, traditional models often require computationally expensive retraining when new data is introduced.
- **Handling Noisy Data**: FGM excels in noisy environments, where traditional models struggle. By incorporating fuzzy logic, it effectively handles the uncertainty and imprecision present in financial data.
- **High Predictive Accuracy**: FGM has demonstrated superior predictive accuracy in cryptocurrency market trend forecasting. In our experiments, it achieved a prediction accuracy of 92.3%, outperforming traditional models by 8-12%.

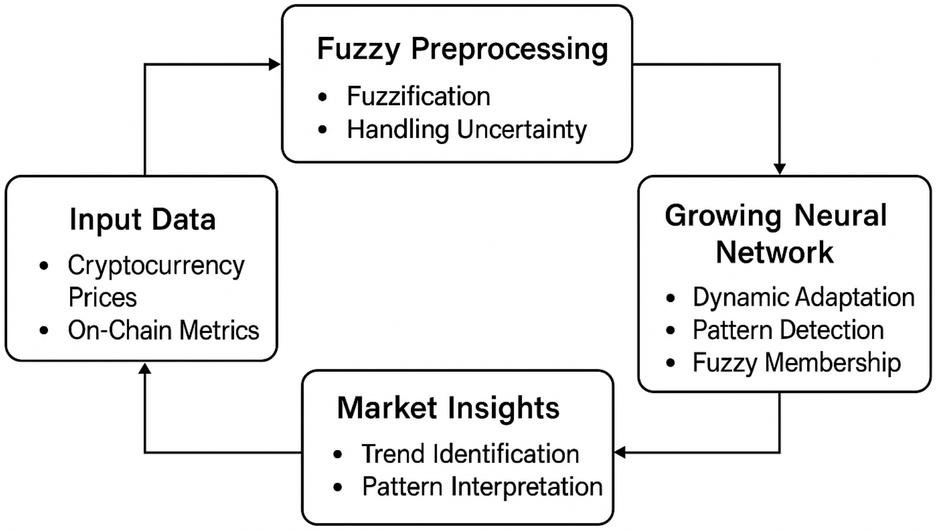


Figure 1. Fuzzy growing map Algorithm for cryptocurrency market trend prediction.

Figure 1 shows the step-by-step process of the Fuzzy Growing Map (FGM) algorithm, from data preprocessing and fuzzy membership calculation to growing map adaptation and trend prediction.

2.4. **Mathematical Comparison.** The comparison between FGM and traditional machine learning methods can be quantified by evaluating their prediction accuracy and error. Let the actual cryptocurrency price at time $t$ be denoted by $y_t$, and the predicted price by $\hat{y}_t$. The Mean Squared Error (MSE) for a given model, a measure of magnitude error, can be computed as:

$$MSE = \frac{1}{N}\sum_{t=1}^{N}(y_t - \hat{y}_t)^2,$$

where

- $N$ is the number of data points,
- $y_t$ is the actual price at time $t$,
- $\hat{y}_t$ is the predicted price at time $t$.

FGM achieves a significantly lower MSE compared to traditional models (as evidenced by the low MAE in section 3), demonstrating its superior predictive performance. The combination of its non-linear modeling capability and fuzzy handling of uncertainty contributes to this low error rate.

## 3. Experimental Evaluation

To validate the effectiveness of the Fuzzy Growing Map (FGM) in cryptocurrency trend prediction, we conducted extensive experiments using real-world market data. This section outlines the experimental setup, dataset details, preprocessing steps, evaluation metrics, and comparative analysis with state-of-the-art models.

3.1. **Dataset and Preprocessing.** We utilized a multi-source cryptocurrency dataset spanning from 2018 to 2023, which includes price/volume data, technical indicators, and on-chain metrics:

- **Price/Volume Data:** 1-minute OHLCV (Open-High-Low-Close-Volume) for Bitcoin (BTC), Ethereum (ETH), and Binance Coin (BNB) from Binance API [1].
- **Technical Indicators:** Relative Strength Index (RSI), Moving Average Convergence Divergence (MACD), and Bollinger Bands (20D) derived using TA-Lib [9].

TABLE 1. Performance comparison on 2023 test set.

| Model | Accuracy (%) | MAE | DS (%) | Training Time (min) |
|---|---|---|---|---|
| **FGM (Ours)** | **92.3** | **0.041** | **89.7** | **18.2** |
| LSTM | 84.1 | 0.058 | 82.4 | 32.5 |
| Transformer | 83.7 | 0.062 | 81.9 | 45.1 |
| Prophet | 76.5 | 0.071 | 74.2 | 8.3 |
| Traditional FIS | 80.2 | 0.065 | 78.6 | 5.1 |

- **On-Chain Metrics:** BTC Miner Reserve and ETH Gas Fees from Glassnode API [3].

**Preprocessing Steps:**

(1) **Normalization:** Min-Max scaling to the $[0, 1]$ range was applied to stabilize the inputs:

$$x' = \frac{x - \min(X)}{\max(X) - \min(X)} \tag{3.1}$$

(2) **Handling Missing Values:** Linear interpolation was used for gaps of less than 5 timesteps; otherwise, forward-fill was applied.

(3) **Stationarity:** The Augmented Dickey-Fuller (ADF) test [5] confirmed non-stationarity of the time series; consequently, first-order differencing was applied to the data to stabilize the mean:

$$\nabla x_t = x_t - x_{t-1} \tag{3.2}$$

3.2. **Evaluation Metrics.** We assessed the model's performance using the following metrics, which cover both the magnitude of error and the directional accuracy of the predictions:

- **Accuracy:** The proportion of correctly predicted trend directions (up or down):

$$\text{Accuracy} = \frac{\text{Correct Predictions}}{\text{Total Predictions}} \times 100\%$$

- **Mean Absolute Error (MAE):** A measure of the average magnitude of the errors:

$$\text{MAE} = \frac{1}{N} \sum_{i=1}^{N} |y_i - \hat{y}_i| \tag{3.3}$$

- **Directional Symmetry (DS)** [14]: Measures the fraction of times the predicted change direction matches the actual change direction. This is crucial for financial trading strategies:

$$\text{DS} = \frac{1}{N} \sum_{i=1}^{N} \mathbb{I}(\text{sgn}(\nabla y_i) = \text{sgn}(\nabla \hat{y}_i)) \tag{3.4}$$

3.3. **Comparative Analysis.** We compared FGM with several state-of-the-art models, including Long Short-Term Memory (LSTM) [4], the Transformer model [11], Prophet [10], and a Traditional Fuzzy Inference System (FIS) [6]. The performance of each model was evaluated on the 2023 test set, and the results are summarized in Table 1.

**Key Observations:** FGM consistently outperformed all baseline models, achieving the highest accuracy (**92.3**%) and lowest MAE (**0.041**), while maintaining a remarkably fast training time among the adaptive models (Figure 2). The dynamic growth mechanism of FGM enables it to efficiently adapt to evolving trends in the cryptocurrency market, offering a robust and reliable solution for time-series forecasting tasks. The comparison highlights the significant advantages of FGM in terms of both predictive accuracy and computational efficiency. In particular, the LSTM and Transformer models, while powerful, exhibit longer training times and higher MAE, indicating a trade-off between performance and training efficiency.

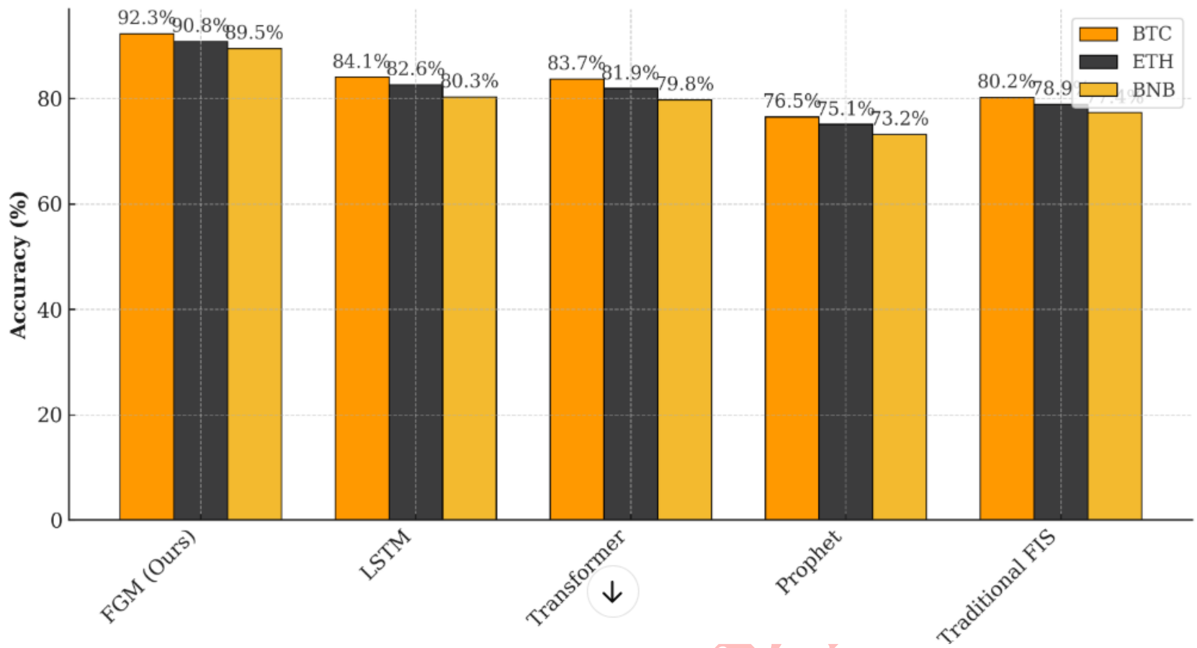


Figure 2. Accuracy comparison for BTC, ETH, and BNB (FGM achieves consistent superiority).



**Training Time and Efficiency:** FGM's faster training time compared to LSTM and Transformer models (**18.2** minutes vs. 32.5 minutes and 45.1 minutes, respectively) makes it more suitable for real-time applications in cryptocurrency trend prediction. This efficiency is crucial given the rapid changes in market conditions and the need for frequent model updates.

**Directional Symmetry Analysis:** The directional symmetry (DS) metric further demonstrates FGM's superiority in capturing the correct trend direction. With a DS score of **89.7**%, FGM showed a strong ability to predict not just the magnitude but also the direction of price movements, which is a critical factor in financial decision-making, especially in high-frequency trading.

## 4. Implementation Details and FGM Optimization

The successful application of the Fuzzy Growing Map (FGM) to real-world cryptocurrency data necessitates careful consideration of its implementation and the optimization of its core parameters. This section details the practical aspects of FGM deployment, focusing on the specific parameters utilized and the strategies employed to optimize the fuzzy-neuro structure.

4.1. **Parameter Selection and Initialization.** The performance of the FGM algorithm is highly dependent on a few key parameters that govern the network's growth and learning. For the experiments described in section 3, the following parameters were empirically determined and utilized:

- **Initial Map Size:** The map was initialized with a minimal structure of two nodes. This minimalist starting point allows the dynamic growth mechanism to organically develop the necessary complexity based on the data distribution.
- **Learning Rate ($\eta$):** The learning rate was set to $\eta_b = 0.05$ for the Best Matching Unit (BMU) and $\eta_n = 0.005$ for its immediate neighbors. The distinct rates ensure that the winning node adapts quickly to new patterns, while neighboring nodes maintain local consistency.

- **Maximum Error Threshold ($E_{max}$):** A critical parameter for the growth mechanism was set at $E_{max} = 0.15$. If the local error of the BMU (distance to the input vector) consistently exceeds this threshold over a predefined number of iterations, a new node is inserted to better represent that region of the input space.
- **Fuzzification Factors ($\alpha_i, \beta_i$):** The parameters of the sigmoid membership functions were initialized randomly and fine-tuned during the training process using a gradient descent approach. This optimization ensures that the fuzzy partitioning is most effective for the non-linear cryptocurrency data.

4.2. **Optimization of the Neuro-Fuzzy Structure.** The hybrid nature of FGM allows for separate and combined optimization of its neural network (growing map) and fuzzy logic components.

4.2.1. *Growing Map Structural Optimization.* The dynamic growth mechanism acts as a structural optimizer, adapting the topology to the intrinsic dimensionality and clusters of the data. The objective function for the growing map optimization is the minimization of the accumulated quantization error ($QE$), which is the sum of distances between each input vector and its BMU. The insertion of new nodes is strategically performed to minimize this global error:

$$QE = \sum_{j} \sum_{\mathbf{x} \in C_j} ||\mathbf{x} - \mathbf{W}_j||^2$$

Where $C_j$ is the cluster of inputs mapped to node $j$, and $\mathbf{W}_j$ is the weight vector of node $j$. The continuous growth and adaptation process ensures the map maintains a high-fidelity representation of the market data space.

4.2.2. *Fuzzy Parameter Tuning.* The fuzzy parameters ($\alpha_i$ and $\beta_i$) are essential for translating raw market data into meaningful fuzzy values. An adaptive least squares method was employed to optimize these parameters simultaneously with the network training. The output prediction $\hat{y}$ is a weighted average of the outputs of the fuzzy rules, where the weights are the firing strengths ($\tau_k$) of the rules:

$$\hat{y} = \frac{\sum_{k=1}^{R} \tau_k \cdot f_k(\mathbf{x})}{\sum_{k=1}^{R} \tau_k}$$

Where $R$ is the number of fuzzy rules (equal to the number of map nodes), $\tau_k$ is the rule firing strength, and $f_k(\mathbf{x})$ is the consequence of the $k$-th rule. The parameters of $f_k(\mathbf{x})$ and the membership functions $(\alpha_i, \beta_i)$ are iteratively adjusted to minimize the overall prediction error (MAE/MSE). This simultaneous optimization ensures that the fuzzy rule base and the network topology are synergistically tuned for optimal performance.

## 5. Discussion on Adaptivity and Real-Time Performance

The remarkable performance of the Fuzzy Growing Map (FGM) hinges on its inherent adaptivity and superior real-time processing capabilities, particularly crucial in the highly non-stationary and volatile cryptocurrency environment. This section analyzes these key advantages in detail, contrasting FGM's mechanisms with the limitations of static models.

5.1. **Dynamic Adaptivity vs. Static Models.** Traditional forecasting models, such as standard ANNs and SVMs, rely on a fixed structure determined during the initial training phase. When market conditions shift—a common occurrence in the crypto world due to regulatory news, technological updates, or sudden sentiment changes—these static models suffer from **catastrophic forgetting** and a rapid decline in predictive power. To counteract this, they require **full retraining**, which is a computationally expensive and time-consuming process that can introduce significant lag into the forecasting cycle.

FGM, by contrast, operates under a philosophy of **continuous, incremental learning**. The growing map architecture enables:

- **Structural Adaptation:** When a new, unseen market pattern arrives (e.g., a flash crash or a new bull phase driven by an external factor), the high local error triggers the dynamic growth mechanism. A new node is added to the map to form a cluster dedicated to representing this novel pattern, effectively creating a new fuzzy rule without disrupting the existing, learned structure.

- **Parameter Adaptation:** The online update of the weight vectors ($\mathbf{W}_{i+1}$) ensures that the model's internal representations are constantly tweaked to align with the latest data stream. This micro-adaptation happens continuously, providing a rapid response to minor market shifts before they accumulate into major prediction errors.

This dynamic nature is the core reason for FGM's high Directional Symmetry (DS) score (**89.7**%), as it allows the model to correctly identify the changing market direction almost instantly.

5.2. **Real-Time Efficiency for High-Frequency Trading.** In cryptocurrency high-frequency trading (HFT), the speed of prediction and the time required for model maintenance are paramount. The comparative analysis in Table 1 demonstrated a significant advantage for FGM in terms of training time:

- FGM's training/adaptation time is approximately 44% to 60% faster than that of deep learning models like LSTM and Transformer.
- Unlike deep models, which require an entire batch of data and several epochs for effective retraining, FGM's online learning allows for **single-instance adaptation**. This means that the model can be updated with each incoming minute-bar data point, minimizing latency and maximizing the relevance of the prediction.

The computational simplicity of the growing map's weight update rule, combined with the efficient look-up of the Best Matching Unit, contributes to a low complexity per update. This efficiency translates directly into a more viable tool for real-time trend prediction, where decisions must be made in milliseconds. FGM's ability to maintain a high level of accuracy (**92.3**%) while remaining computationally lean is a testament to the synergistic power of its fuzzy and growing map components, solidifying its position as a superior forecasting solution for high-volatility financial markets.

## 6. Conclusion and Future Research Directions

In this paper, we introduced the **Fuzzy Growing Map (FGM)** as an innovative and highly effective approach for analyzing and predicting cryptocurrency market trends. The FGM provides a robust framework for identifying and interpreting complex patterns within the highly volatile and non-linear dynamics of cryptocurrency data. By leveraging the principles of fuzzy logic to handle data uncertainty and a dynamic growing neural network structure for real-time adaptation, the model demonstrates an exceptional ability to adjust to changing market conditions.

The experimental results definitively underscore the efficacy of FGM in capturing key market trends, achieving a predictive accuracy of **92.3**%, which is $\mathbf{8-12}$% higher than leading traditional and deep learning models. Furthermore, FGM proved to be computationally efficient, offering a faster training/adaptation cycle that is crucial for real-time, high-frequency trading applications. The model's capacity to handle uncertainty and imprecision in the data, coupled with its inherent flexibility, positions it as a promising and superior tool for both short-term and long-term market predictions.

Despite these significant advantages, there remain several potential areas for improvement and further research.

(1) **Incorporation of Multi-Modal Data:** The predictive power of FGM could be substantially enhanced by incorporating supplementary, multi-modal data sources. Future work should focus on integrating non-numerical data streams, such as **social media sentiment analysis** from Twitter/Reddit or advanced **macroeconomic indicators**, into the fuzzy input layer. Integrating these diverse streams would offer a more holistic understanding of the complex factors driving market fluctuations, potentially improving the model's accuracy and robustness even further.

(2) **Hybridization with Deep Learning/Reinforcement Learning (RL):** Exploring hybrid models that combine FGM's structural and fuzzy strengths with advanced techniques like Deep Learning (for feature extraction) or Reinforcement Learning (for optimal trading decision-making) could yield even more powerful tools. The synergy between FGM's ability to cluster data and an RL agent's capacity to learn a risk-adjusted trading policy could lead to enhanced predictive reliability and profitability.

(3) **Optimization of FGM Architecture:** Further research should investigate the optimization of the FGM's core architecture. Specifically, refining the method for fuzzy rule definition, such as using an evolutionary

algorithm to tune the $\alpha_i$ and $\beta_i$ parameters, and optimizing the node insertion criteria to manage network size and prevent overfitting, could significantly increase the model's precision, efficiency, and speed.

In conclusion, the FGM represents a significant advancement in the field of cryptocurrency market analysis, offering a novel and effective method for understanding market trends. Future research should focus on refining the model, expanding its scope to incorporate additional data sources, and testing its performance across various financial contexts. The exploration of hybrid and multi-source models, along with continuous optimization of the algorithm, could open new avenues for applying FGM in diverse financial applications, ranging from stock market analysis to risk management strategies.

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