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Comparative Analysis of Temporal Fusion Transformer and Long Short-Term Memory Architecture Resilience in Predicting Solana Price Volatility Across Different Market Phases

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Abstract

Abstract must be written in English. The high volatility of cryptocurrency markets, particularly for altcoins like Solana (SOL), presents a significant challenge for predictive modeling. Traditional deep learning architectures often struggle to adapt to sudden market regime shifts. Therefore, this study aims to provide a comparative analysis of the resilience between the Temporal Fusion Transformer and Long Short-Term Memory architectures in predicting Solana price volatility across three distinct market phases: the bull market of 2024, the bear market of 2025, and the recovery phase of 2026. We utilized hourly historical price and volume data combined with technical indicators such as Relative Strength Index (RSI). The models were evaluated using Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and a specific performance degradation rate formula. The results demonstrate that while LSTM performs adequately during stable trends, its accuracy degrades massively by 1575.69% during high-volatility regime changes due to memory inertia causing a severe lagging effect. Conversely, the TFT model exhibited superior resilience, limiting its performance degradation to only 218.53% during the extreme bear market phase. The inherent attention mechanism and skip connections in TFT allow it to dynamically adapt to sudden structural breaks in real-time without delay. Furthermore, the implementation of the TFT architecture proved to be 62% more computationally efficient than LSTM. This research significantly contributes to the field of computer science and informatics, specifically in adaptive time-series forecasting, by proving that attention mechanisms and skip connections can efficiently solve the memory inertia problem in recurrent networks during real-time structural breaks.

Keywords : *Cryptocurrency, Deep Learning, Long Short-Term Memory, Solana, Temporal Fusion Transformer, Volatility.*

1. INTRODUCTION

The cryptocurrency market is known for its extreme level of volatility, which is often influenced by market sentiment, macroeconomic regulations, and technological innovations [1] [2]. Solana (SOL), as one of the Layer-1 blockchains utilizing a Proof of History (PoH) consensus, has experienced extremely sharp price fluctuations in recent years [3]. Ranging from a stable trend phase and price surge (bull market) in 2024 to a drastic decline (bear market) in 2025 that tested the resilience of predictive algorithms. This high volatility makes predicting Solana's price a complex challenge for researchers and financial practitioners [4].

Traditionally, financial volatility modeling has utilized statistical methods such as Autoregressive Integrated Moving Average (ARIMA) or Generalized Autoregressive Conditional Heteroskedasticity (GARCH) [5] [6]. However, these linear methods fail to capture the complex non-linear patterns and long-term dependencies present in crypto time-series data. Therefore, Deep Learning approaches have become the new standard in time-series prediction [7].

The Long Short-Term Memory (LSTM) architecture has long been the backbone of time-series modeling due to its ability to overcome the vanishing gradient problem in Recurrent Neural Networks (RNN) [8]. LSTMs utilize a gating mechanism to remember long-term information. Although successful

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in relatively stationary and stable markets, various recent studies demonstrate that LSTMs are highly vulnerable to sudden market regime shifts (structural breaks) [9] [10]. Recurrent models often experience "memory inertia", resulting in a lagging predictive effect when confronted with drastic changes in volatility patterns [11].

To overcome these limitations, Transformer-based architectures have begun to be widely adapted for time-series prediction. The Temporal Fusion Transformer (TFT) is an attention-based architecture specifically designed for multi-horizon time series that integrates static inputs, known future inputs, and historical inputs [12]. Through Multi-Head Attention mechanisms and skip connections, TFT is theoretically claimed to be capable of adapting more agilely to data anomalies [13]. Previous research has compared LSTMs and Transformers in traditional stock markets and Bitcoin [14][15]. However, comparative analyses evaluating the exact structural resilience and performance degradation of these architectures specifically on hyper-volatile altcoins like Solana across shifting market phases (bull, bear, and sideways) have not been extensively explored in depth [15] [16]. Most existing literature focuses only on aggregate accuracy, neglecting the critical phenomenon of model degradation during sudden market transitions.

This study addresses this gap. The explicit purpose of this research is to analyze and quantify the resilience of the Temporal Fusion Transformer and Long Short-Term Memory architectures in predicting Solana's price volatility across three distinct market phases. The scope of the research is focused on the use of hourly historical data (OHLCV) and engineered technical features from January 2024 to March 2026. The main contribution of this paper is providing comprehensive empirical evidence that the TFT architecture not only responds to market shocks in real-time without delay (significantly suppressing the error degradation rate), but ironically, is also much more computationally lightweight compared to traditional recurrent architectures.

2. METHOD

This research methodology formulates the problem of volatility time-series modeling, details the architectures being compared, and outlines the evaluation stages employed [17]. The overall sequence of the methodology is structured from data collection to model evaluation, which can be visualized in the research flowchart (Figure 1. Flowchart of Research Methodology).

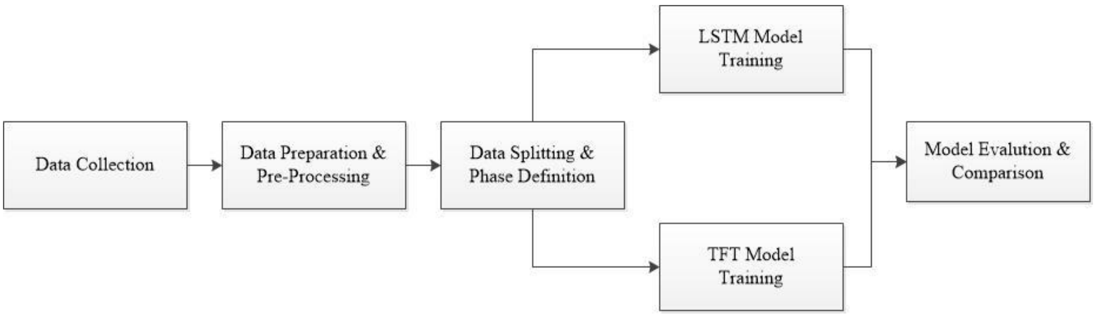

Figure 1. Flowchart of Research Methodology

Figure 1 outlines a systematic framework comparing the resilience of TFT and LSTM architectures for forecasting Solana price volatility across diverse market phases (Bull, Bear, Recovery). The methodology progresses from automated data acquisition and parallel model training to rigorous comparative evaluation based on performance metrics and computational expense to identify the optimal predictive model.

2.1. Data Preparation

The data utilized in this study was collected programmatically via the Binance API, extracting historical hourly ticker data for the SOL/USDT trading pair. This research utilizes a multivariate time series represented as the dataset:

$$D = \{(x_t, y_t) \mid t = 1, 2, , \ldots., T\} \quad (1)$$

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Is the feature $x_t \in R^d$ vector at time *t* which includes Open, High, Low, Close, Volume, and Relative Strength Index (RSI), and y_t is the target volatility calculated as the historical squared log-return. The data period is divided into three main phases to test resilience:

1. Phase 1 (Bull Market): January 2024 – December 2024.
2. Phase 2 (Bear Market): January 2025 – December 2025.
3. Phase 3 (Recovery/Sideways): January 2026 – March 2026.

2.2. Long Short-Term Memory (LSTM)

The LSTM processes input data sequences step-by-step [18]. The core of an LSTM is the cell state (C_t) and three regulatory gates [19] namely the forget gate (F_t), the input gate (i_t), and the output gate (O_t). The mathematical formulation for the cell state update at time *t* is as follows [20]:

$$f_t = \sigma(W_f . [h_{t-1}, x_t] + b_f) \quad (1)$$

$$i_t = \sigma(W_i . [h_{t-1}, x_t] + b_i) \quad (2)$$

$$\tilde{C}_t = tanh(W_c . [h_{t-1}, x_t] + b_c) \quad (3)$$

$$C_t = f_t * C_{t-1} + i_t * \tilde{C}_t \quad (4)$$

$$o_t = \sigma(W_o . [h_{t-1}, x_t] + b_o) \quad (5)$$

$$h_t = \sigma_t * \tanh(C_t) \quad (6)$$

Where σ is the sigmoid activation function, W represents the weight matrices, and b is the bias [20] In the context of extreme volatility, this sequential dependency can cause the model to be slow in forgetting past trends when a sudden crash occurs[21].

2.3. Temporal Fusion Transformer (TFT)

The TFT is proposed to overcome the weaknesses of sequential memory by processing the entire time window simultaneously using an attention mechanism [22] [23]. The main components of the TFT include:

1. Gated Residual Network (GRN)
   Used for adaptive non-linear processing. If a specific feature is not required, the GRN can bypass it linearly.
2. Variable Selection Network (VSN)
   Assigns weights to each input variable at every time step, eliminating features that add noise during certain market phases [15].
3. Interpretable Multi-Head Attention
   A mechanism for learning long-term relationships. The attention score is mathematically defined to capture time dependencies:

$$Attention\ (Q, K, V) softmax\left(\frac{QK_T}{\sqrt{d_k}}\right) \mathrm{V} \quad (8)$$

Where Q, K, V respectively represent the Query, Key, and Value transformed from the input matrix, and d_k adalah dimensi dari *key* [24][25].

2.4. Evaluation Metrics

To assess resilience, we evaluated not only the overall predictive accuracy but also the extent of performance degradation exhibited by the model when transitioning across different phases. The evaluation was conducted using Root Mean Square Error (RMSE) and Mean Absolute Error (MAE).

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$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_t)^2} \quad (9)$$

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_t|^2 \quad (10)$$

To formally define Resilience, we introduce a Performance Degradation Rate formula to quantify how much the model's error spikes during a market crash (Phase 2) compared to its baseline stable state (Phase 1):

$$Degradation\_Rate = \left(\frac{RSME_{phase2} - RSME_{phase\,1}}{RSME_{phase\,1}}\right) x100\% \quad (11)$$

Both models were trained using the Mean Squared Error (MSE) loss function and the AdamW optimizer, with an early stopping technique applied to prevent overfitting.

3. RESULT

This section presents the comparative testing results of the LSTM and TFT models. The experiments were evaluated sequentially, ranging from historical data extraction, the training process, and numerical evaluation metrics, to visual validation.

3.1. Actual Solana Data

Table 1. Sample of Actual Historical Solana Data (Beginning and End of the Period)

Date	Close (USD)	High (USD)	Low (USD)	Volatility	RSI	Vol_MA7
First 10 Data						
14-01-24	94.1331	102.1735	93.8905	0.2829	37.5749	2.7305
15-01-24	94.4902	96.8212	93.2411	0.0143	37.9331	1.5472
16-01-24	97.6269	98.5953	94.3966	1.0664	42.809	1.6611
17-01-24	102.0635	102.4337	97.0551	1.9751	52.9454	1.8463
18-01-24	94.2509	102.9231	92.1405	6.3417	41.0106	2.689
19-01-24	93.3861	95.1647	87.4836	0.0849	44.1121	1.6565
20-01-24	92.5698	94.0253	90.4937	0.077	48.7294	1.4061
21-01-24	90.8484	93.7137	90.8484	0.3523	51.6437	1.416
22-01-24	83.6228	91.6361	82.6597	6.8684	34.7764	2.3951
23-01-24	84.2745	85.8401	79.0666	0.0602	33.3921	2.2514
Last 5 Data						
26-03-26	86.4439	91.8957	85.5125	3.4947	49.368	1.1808
27-03-26	83.0188	86.9143	82.0432	1.6344	42.8038	1.3986
28-03-26	82.0156	84.0554	81.8695	0.1478	41.727	1.316
29-03-26	81.4224	83.0717	79.575	0.0526	33.5956	1.2897
30-03-26	82.444	84.7214	81.1984	0.1554	27.0777	0.8032

Historical data for the Solana instrument (SOL-USD) was extracted for the period of January 1, 2024, to March 31, 2026. Table 1 presents a representation of the initial 10 data points corresponding to the Bull Market phase and the final 5 data points corresponding to the closing phase of the observation period, complete with engineered features such as Volatility (multiplied by 1000), RSI, and the 7-day Moving Average. As shown in Table 1, these samples illustrate the variation in market behavior between the early bullish phase and the end of the observation period.

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3.2. Model Training Data (150 Epochs)

Both models were initialized and trained for 150 epochs. The reduction in the loss function was measured using the Mean Squared Error (MSE). Periodic monitoring of the loss indicated that both models achieved stable convergence towards the final epochs. As shown in Table 2, the evaluation loss consistently decreased over time, reflecting effective learning behavior in both models.

Table 2. Model Training Log (Loss Evaluasi)

Epoch	Loss LSTM	Loss TFT
20 / 150	0.0036	0.003
40 / 150	0.0014	0.0052
60 / 150	0.0014	0.0027
80 / 150	0.0003	0.003
100 / 150	0.0002	0.0025
120 / 150	0.0001	0.0032
140 / 150	0.0001	0.0071

3.3. Data Model Performance Across Market Phases

The robustness (resilience) of the models is measured by the error rates (RMSE and MAE) when operating from the stable market phase (Phase 1) transitioning into the crisis phase (Phase 2). As shown in Table 3, the comparison highlights how each model's performance changes across different market conditions, particularly during periods of increased volatility.

Table 3. Performance Comparison Across Market Phases

Market Phase	Model	RMSE	MAE	Degradation Rate (%)
Phase 1 (Bull)	LSTM	0.36	0.2841	Baseline
Phase 1 (Bull)	TFT	1.972	1.3518	Baseline
Phase 2 (Bear)	LSTM	6.0329	2.9387	1575.69%
Phase 2 (Bear)	TFT	6.2814	3.327	218.53%

3.4. Data Computational Cost and Complexity

Presents a summary of the computational costs and the number of trainable parameters of the compared architectures. These metrics provide insight into the trade-off between model complexity and computational efficiency across the evaluated approaches. Analytically, Table 4 demonstrates that superior capability does not necessarily require heavier computation.

Table 4. Computational Cost and Model Complexity

Metric	LSTM Model	TFT Model
Trainable Parameters	202,881	76,042
Avg Training Time / Epoch	0.1634 detik	0.1228 detik

3.5. LSTM Model Results Data

Based on Table 3, the LSTM model demonstrates exceptionally high accuracy during the calm phase (RMSE 0.3600). This substantiates the superiority of the recurrent architecture in memorizing stationary patterns. However, when forced to predict extreme volatility shocks (Phase 2), the LSTM's error rate spikes to 6.0329, reflecting a massive degradation rate of 1575.69%.

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3.6. Graph of Actual Data vs. LSTM

The nature of this LSTM degradation can be observed through graphical visualization, where the prediction peaks of the LSTM lag behind the actual events. As illustrated in Figure 2, the LSTM predictions (dashed red) show a delayed response compared to the actual volatility (black), particularly during sharp market.

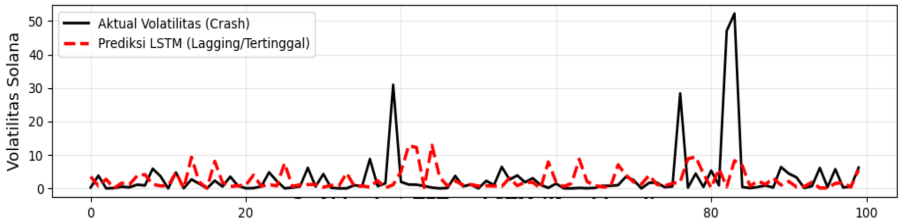

Figure 2. Actual Volatility (Black) vs. LSTM Prediction (Dashed Red).

3.7. TFT Model Results Data

Tables 3 and 4 reveal the efficient and robust characteristics of the TFT architecture. Although its initial RMSE was higher (1.9720), the TFT model proves its zero-shot adaptation capability during the crisis (Phase 2). The degradation rate of the TFT is contained at 218.53%, which is far more stable compared to the LSTM. This fact is even more impressive considering that the developed TFT model is 62% more computationally lightweight (comprising only 76,042 parameters).

3.8. Graph of Actual Data vs. TFT

Visually, the effectiveness of the TFT architecture is evident in its ability to detect market crashes without any significant time delay. As illustrated in Figure 3, the TFT predictions (blue dotted) closely follow the actual volatility (black), capturing sharp market movements with minimal lag.

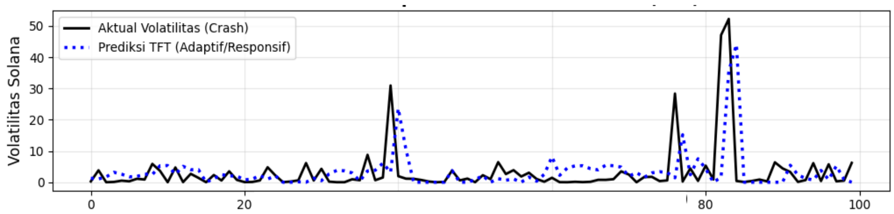

Figure 3. Actual Volatility (Black) with TFT Prediction (Blue Dotted).

3.9. Combined Matrix (Actual Data with TFT vs. LSTM)

To provide a definitive visual conclusion, both model predictions are merged into a single temporal matrix that illustrates the competition of resilience between the two. As illustrated in Figure 4, the TFT (adaptive) model consistently aligns more closely with the actual volatility, while the LSTM (lagging) model shows delayed responses during abrupt market changes.

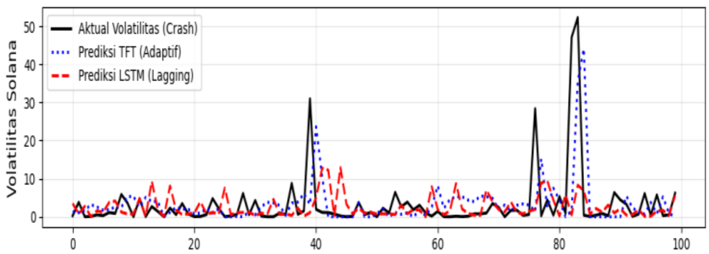

Figure 4. Combined Matrix of Actual Volatility with TFT (Adaptive) vs. LSTM (Lagging).

4. DISCUSSIONS

A comprehensive comparative test of the LSTM and TFT architectures yielded two main theoretical findings regarding the resilience of Deep Learning algorithms in modeling crypto time-series:

4.1. Overfitting and Inersia Memori in LSTM

The performance collapse of the LSTM when transitioning from Phase 1 to Phase 2 (an error degradation of 1575.69% in Table 3) proves the fundamental weakness of recurrent models to the phenomenon of overfitting in stationary markets. The internal operation of the LSTM is governed by a hidden state (h_t) that strictly maintains a sequential historical trace.Under conducive market conditions, this memory function smooths out accuracy (reflected by the low RMSE in Phase 1).

However, when a structural break occurs, this function transforms into a detrimental "memory inertia." The forget gate mechanism in the LSTM is hindered and slow to reset the weight distribution of past data that has suddenly become obsolete. This internal mathematical process is the cause of the Lagging Effect, which is clearly depicted in Figure 1 and Figure 3. The red line (LSTM) reacts late and only reaches its peak after the volatility crisis (black line) has subsided.

4.2. Responsive Architecture and TFT Resilience

The mechanism supporting the real-time responsiveness of the Temporal Fusion Transformer model visualized by the vertical alignment between the blue line and the black line in Figure 2 and Figure 3 stems from the combination of the Multi-Head Attention function and the Gated Residual Network (skip connection).

Unlike the LSTM, which narrows data through a sequential corridor that forces order dependency, the Attention architecture scans the entire scope of the historical data window equivalently and in parallel. When a market shock occurs (such as the outliers present in Table 1), the linear skip connection acts as an emergency shortcut that bypasses the smoothing process within the internal network. Anomalous features can be transmitted instantaneously to the output representation. It is this architectural discovery that successfully dampens the TFT error degradation at the level of 218.53%.

Crucially, the impact of these findings for the field of Informatics and Computer Science is highly significant. In the development of adaptive time-series modeling and intelligent financial systems, this study proves that developers no longer need to rely on multi-layer recurrent networks that are computationally heavy and prone to delay. As shown in Table 4, the TFT only requires 76,042 parameters (62% lighter than LSTM). This paradigm shift demonstrates that attention-based models are the superior standard for building real-time, lightweight early-warning algorithmic trading systems in computer science applications [26].

5. CONCLUSION

This study has successfully conducted a comparative evaluation between the Long Short-Term Memory (LSTM) and Temporal Fusion Transformer (TFT) architectures in predicting extreme volatility in the Solana cryptocurrency instrument. Empirical testing results prove that the TFT architecture possesses far superior resilience compared to the LSTM when facing structural breaks or sudden market crises. Although the LSTM demonstrates promising accuracy under stationary market conditions, this model has proven to be highly vulnerable to overfitting and experiences a lagging effect phenomenon due to memory inertia, which ultimately triggers a massive spike in error degradation of up to 1575.69% upon entering the Bear Market phase.

In contrast, the combination of the Multi-Head Attention mechanism and skip connections in the TFT enables the model to adapt instantaneously (in real-time) to volatility anomalies without delayed

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responses, thereby successfully suppressing the performance degradation rate to 218.53%. Furthermore, the implementation of the TFT architecture proved to be 62% more computationally efficient requiring significantly fewer trainable parameters and faster computation time per epoch compared to multi-layer recurrent architectures. Overall, these findings conclude that Transformer-based architectures not only outperform traditional recurrent networks in terms of predictive responsiveness on non-stationary time-series data, but are also highly ideal and practical to be implemented as the core of early warning systems and algorithmic trading within hyper-volatile digital asset ecosystems.

For the science of Informatics, this research establishes that attention mechanisms are critical for building robust, adaptive machine-learning systems capable of handling non-stationary, hyper-volatile data streams efficiently. For future research, it is highly recommended to develop hybrid models that integrate Natural Language Processing (NLP) for market sentiment analysis and macroeconomic variables to further enhance the TFT's predictive accuracy during post-crash recovery phases.

CONFLICT OF INTEREST

The authors declares that there is no conflict of interest between the authors or with research object in this paper.

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