JOURNAL OF EMERGING TECHNOLOGY AND DIGITAL TRANSFORMATION

ONLINE ISSN
3006-9726

PRINT ISSN
3006-9718

VOLUME . 4 ISSUE . 2 (2025)

Predicting Crypto Currency Return on Investment Using Advanced Deep Learning Techniques

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Received	Approved	Published
13th March 2025	12th June 2025	15th June 2025

Abstract:

The rapid growth and volatility of cryptocurrencies like Bitcoin, Ethereum, Cardano, and Solana have transformed global finance, but their unpredictable price behavior poses significant forecasting challenges. This research introduces a real-time, ROI-focused prediction framework using a hybrid deep learning model that integrates Gated Recurrent Units (GRU) and Transformer encoders. Designed for ultra-short-term (180-minute) price forecasting, the model not only predicts future prices but also estimates Return on Investment (ROI), providing actionable insights for intraday and algorithmic trading. Minute-level data is collected via the CoinGecko API and preprocessed using techniques like normalization and sliding windows. The GRU captures short-term dependencies efficiently, while the Transformer component models broader market trends using self-attention. Implemented in Python with PyTorch and evaluated using RMSE, MAE, MAPE, MSE, and R^2, the hybrid model consistently outperforms a Vanilla RNN in both accuracy and ROI-based profitability simulations. The research addresses key gaps in literature by offering a practical, ROI-integrated prediction system, enabling real-time asset ranking and decision-making in highly dynamic trading environments.

Keywords: *Cryptocurrency/ Return on Investment (ROI), Deep Learning, GRU (Gated Recurrent Unit), Transformer Encoder, Hybrid Model, Time-Series Forecasting, Algorithmic Trading Earth Engine, Financial Prediction, Real-Time Data Analysis*

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3006-9726
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Introduction

The rise of cryptocurrencies has introduced a paradigm shift in the global financial system. These digital or virtual currencies, secured by cryptographic techniques and operating on decentralized blockchain networks, ensure transactional transparency, immutability, and resistance to manipulation. Since the inception of Bitcoin in 2009 by the pseudonymous figure Satoshi Nakamoto, the cryptocurrency market has evolved significantly, encompassing thousands of digital assets such as Ethereum, Litecoin, Ripple, and Cardano. These assets can be broadly categorized into **coins**, like Bitcoin, used as a medium of exchange, and **tokens**, such as Ether, designed for specific blockchain-based applications.

Despite their technological promise, cryptocurrencies remain highly volatile, with their prices influenced by various factors including market sentiment, regulatory changes, liquidity levels, and speculative trading. This extreme price variability presents both lucrative opportunities and significant risks for investors, particularly those involved in short-term or high-frequency trading. In such a dynamic market, **Return on Investment (ROI)** becomes a critical performance metric for assessing asset profitability.

Accurate prediction of cryptocurrency prices is essential for making timely and informed investment decisions. Traditional forecasting methods and early deep learning models—such as Recurrent Neural Networks (RNNs) and Long Short-Term Memory networks (LSTMs)—have demonstrated potential in modeling time-series financial data. However, these models often depend on static historical data, focus primarily on price trends, and typically lack real-time predictive capabilities. Moreover, they often do not incorporate ROI directly into their outputs, limiting their practical relevance in fast-paced trading environments.

Recent advancements in deep learning, particularly with models like **Gated Recurrent Units (GRUs)** and **Transformer architectures,** offer improved performance in sequence modeling and long-range dependency handling. These models have shown exceptional results in various time-series forecasting applications and present new opportunities for enhancing financial predictive systems.

This research proposes a novel **real-time ROI prediction framework** that addresses the limitations of previous approaches by integrating live price data from the CoinGecko API with a **hybrid deep learning model.** This model combines the sequence-tracking efficiency of GRUs with the contextual depth of Transformer encoders. It is specifically designed to forecast short-term price movements—within a 180-minute window—and translate these forecasts into ROI estimates to aid high-frequency investment decisions.

The key contributions of this study are fourfold:

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3006-9726
PRINT ISSN
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1. Development of a real-time forecasting system using live market data.
2. Implementation of a GRU–Transformer hybrid model tailored for short-term crypto analysis.
3. Integration of an ROI computation layer for actionable investment insights.
4. Comparative evaluation of the proposed hybrid model against a baseline Vanilla RNN.

The primary objectives are to preprocess live data, predict near-future prices, estimate ROI, and identify the most profitable cryptocurrency in short-term scenarios. By enabling data-driven, minute-level decision-making, this framework fulfills a critical need in volatile crypto markets.

The broader significance of this research lies in its attempt to bridge the gap between theoretical price forecasting and practical investment applications. It provides a reusable and scalable design for future real-time financial systems, supports decision-making in high-frequency environments, and establishes a benchmark for ROI-driven deep learning models in cryptocurrency trading.

The scope of the study is limited to short-term (180-minute) real-time forecasting for four major cryptocurrencies: Bitcoin, Ethereum, Cardano, and Solana. It does not extend to long-term market behavior, portfolio optimization, or less prominent digital assets.

Methodology

This study proposes a hybrid deep learning model (GRU + Transformer) for short-term cryptocurrency price prediction, with a comparison to a baseline Vanilla RNN model. The aim is to assess not only the predictive accuracy using standard metrics (e.g., RMSE, MAE, R^2) but also the practical relevance through ROI simulation. The methodology encompasses data collection, preprocessing, model architecture, training strategies, and evaluation procedures for four major cryptocurrencies: Bitcoin, Ethereum, Cardano, and Solana.

A. Data Collection and Preprocessing

1) Data Source and Retrieval

The data collection process involved obtaining minute-level price and volume data were acquired from CoinGecko using its RESTful API. Each coin's historical and live data were fetched for 24-hour intervals at one-minute resolution. This raw data was then parsed and transformed into structured pandas DataFrames were done using Python's requests, Json, and datetime libraries.

2) Cleaning and Aggregation

The data was validated to remove duplicate timestamps and misalignments. Each coin's dataset was standardized and merged with volume information to create a consistent time-series with three key columns: Time, Price, and Volume.

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All timestamps were converted to timezone-aware formats.

3) Preprocessing Pipeline

To ensure the data was suitable for effective model training and prediction, a structured preprocessing pipeline was applied to the live price data of selected cryptocurrencies. The first step involved normalization, where raw price values were scaled to a fixed range of [0, 1] using the MinMaxScaler technique. This step was crucial to prevent large numerical disparities from skewing the learning process and to accelerate the convergence of the deep learning models.

Next, sequence generation was carried out using a sliding window approach. Specifically, a window of 30 consecutive minutes of historical data was used to predict the price for the next (31st) minute. This method allowed the model to learn temporal dependencies within short-term trends, which is particularly important in high-frequency trading scenarios.

For model evaluation, the dataset was partitioned into training and testing sets through a chronological train-test split. The most recent 180 minutes of data were reserved exclusively for testing purposes to evaluate the model's performance on truly unseen and recent data, simulating a real-time forecasting environment. The remainder of the dataset was used for training, ensuring no data leakage occurred from the future into the past.

Finally, the input data was reshaped into multi-dimensional tensors to be compatible with the input requirements of PyTorch-based recurrent neural network architectures. Each input sequence was formatted as a 3D tensor of shape *(batch_size, sequence_length, features)*, ensuring smooth integration with the GRU and Transformer-based models used in this study. This preprocessing pipeline played a critical role in structuring the raw market data into a format that could be effectively leveraged by the deep learning framework for accurate short-term ROI prediction.

C. Model Architectures

1) Vanilla RNN

The Vanilla Recurrent Neural Network (RNN) is the most basic type of recurrent model used to handle sequential data by maintaining a hidden state that carries information from one time step to the next. At each time step, it takes the current input and the hidden state from the previous time step to compute a new hidden state. This enables the model to capture short-term dependencies within the sequence. The hidden state is updated using a weighted combination of the current input and the previous hidden state, passed through a non-linear activation function such as tanh. The optional output at each time step can be derived from the hidden state. While simple and computationally efficient, Vanilla RNNs struggle with long sequences due to the vanishing gradient problem, which limits their ability to retain long-term information.

The hidden state is computed as:

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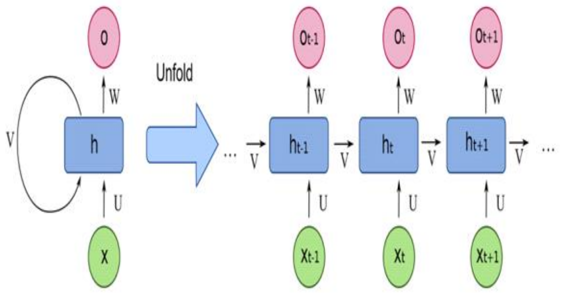
$$h_t = \tanh(W_{xh}x_t + W_{hh}h_{t-1} + b_h)$$

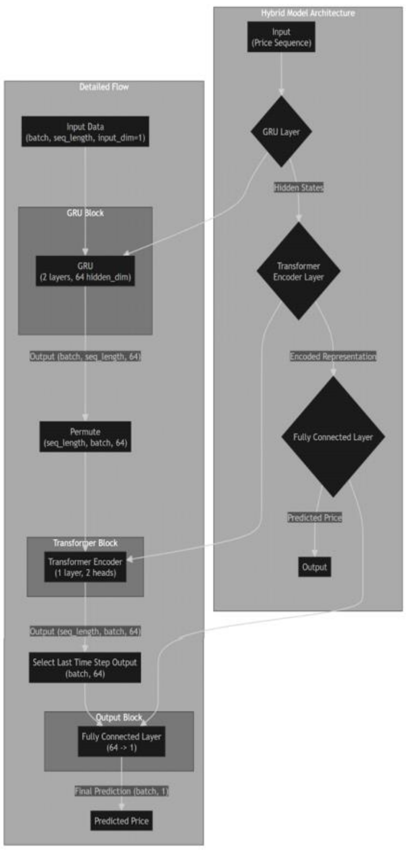
The output (if used) is computed as:

$$y_t = W_{hy}h_t + b_y$$



2) Proposed Hybrid Model (GRU + Transformer)

The proposed hybrid model combines the strengths of Gated Recurrent Units (GRUs) and Transformer Encoders to effectively predict cryptocurrency prices by learning both short-term and long-term dependencies in sequential data. The architecture begins with two stacked GRU layers, each with a hidden size of 64. These GRU layers are responsible for capturing local temporal patterns in the input sequence, such as short-term price movements or momentum. GRUs are particularly effective in modeling short-range dependencies due to their gating mechanisms, which help mitigate the vanishing gradient problem commonly seen in vanilla RNNs. Once the temporal information is processed by the GRUs, their outputs are passed to a Transformer Encoder. The Transformer component is configured with a model dimension (`d_model`) of 64, 2 attention heads (`nhead`), and a feedforward dimension of 128 with a dropout rate of 0.1. The Transformer utilizes self-attention mechanisms to weigh the importance of each time step relative to others, enabling the model to learn global dependencies and long-range interactions in the financial time series. This is especially important in financial data, where events occurring far apart in time can still have meaningful correlations. After the Transformer processing, the output is flattened or pooled and passed through a fully connected dense layer, which generates the final predicted price. This combination of GRUs for short-term dynamics and Transformers for long-term context creates a robust architecture capable of dealing with noisy, nonlinear, and highly volatile financial signals.



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D. Tools and Frameworks

- **Python 3.10**: For scripting and orchestration.
- **PyTorch**: Core framework for deep learning model construction.
- **Pandas / NumPy**: Data handling and numerical operations.
- **Scikit-learn**: Normalization and metric evaluation.
- **Plotly**: Interactive visualization of predicted vs. actual prices.
- **Google Colab**: GPU-accelerated environment for training.
- **CoinGecko API**: Source of real-time and historical crypto data.

E. Training Strategy

1) Loss Function and Optimizer

- **Loss**: Mean Squared Error (MSE) was used to penalize large deviations.
- **Optimizer**: Adam optimizer with learning rate of 0.001 was employed due to its adaptive capabilities and faster convergence.

2) Training Loop

Models were trained over 100 epochs with a batch size of 1 to preserve sequence order. Each epoch consisted of forward propagation, loss calculation, backpropagation, and weight update. Models were trained and saved separately for each coin.

F. Evaluation Metrics

To ensure rigorous assessment, five primary metrics were computed on the test set:

1. **Root Mean Squared Error (RMSE)** – penalizes larger deviations.
2. **Mean Absolute Error (MAE)** – offers robustness against outliers.
3. **R^2 Score (Coefficient of Determination)** – measures the proportion of variance explained.
4. **Mean Absolute Percentage Error (MAPE)** – quantifies relative error in percentage.
5. **Pearson Correlation Coefficient** – evaluates the linear relationship between predicted and actual values.

Predictions were inverse-transformed to actual price values before computing these metrics, ensuring financial interpretability.

G. Validation and Error Analysis

A hold-out validation method was used to simulate real-world forecasting, with strict separation of

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3006-9726
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training and testing timelines. Error analysis included:

- Residual plots
- Error histograms
- Performance comparison across different coins
- ROI impact visualization

This multi-angle evaluation facilitated understanding both statistical accuracy and practical trading implications.

Results and Discussion

This section presents a comparative evaluation of two deep learning models—Vanilla RNN and Hybrid (GRU + Transformer)—applied to short-term cryptocurrency price prediction. The models were tested across four major assets: Bitcoin (BTC), Ethereum (ETH), Cardano (ADA), and Solana (SOL). Key performance metrics including MSE, RMSE, MAE, R^2, Accuracy, and Pearson correlation coefficient were analyzed, with an added focus on ROI (Return on Investment) to assess real-world applicability.

B. Training and Model Comparison

1) Vanilla RNN

The Vanilla RNN, used as a baseline model, was structured with two recurrent layers and a final dense output layer. It effectively captured short-term patterns but suffered from overfitting in volatile phases. Despite lower training loss and faster convergence, it was less robust during testing.

2) Hybrid GRU + Transformer Model

The hybrid model integrated GRU for temporal encoding and Transformer layers for self-attention-based context learning. Though it showed slower initial convergence, it consistently outperformed the RNN in generalization and long-term dependency modeling, particularly under volatility.

3) Training Setup

Both models were trained over 100 epochs using the Adam optimizer and MSE loss, with uniform configurations to ensure fairness. Training loss was logged periodically and GPU resources were utilized to accelerate convergence.

C. Quantitative Evaluation

Mean Squared Error (MSE)

MSE measures the average of the squares of the differences between predicted values and actual (true) values. It's a common metric for evaluating regression models.

Formula:

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

R^2 Score (Coefficient of Determination)

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R^2 measures how well the predicted values explain the variability of the actual data. It tells you the proportion of the variance in the dependent variable that is predictable from the independent variables.

Formula:

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

Pearson's Correlation Coefficient (Pearson R)

Pearson R measures the **linear correlation** between the actual and predicted values. It shows both the strength and direction of a linear relationship.

Formula:

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

Summary Table

Metric	**Measures**	**Ideal Value**	**Range**
MSE	Average squared prediction error	0	[0, ∞)
R² Score	Proportion of explained variance	1	(-∞, 1]
Pearson R	Strength of linear correlation	±1	[-1, 1]

Evaluation metrics showed strong performance across both models, with the Hybrid model generally outperforming RNN in stability and predictive power:

Metric	**RNN (avg)**	**Hybrid (avg)**
MSE	19487.29	19058.91
Accuracy (100 – MAPE)	99.80%	99.90%
R² Score	0.83725	0.8406
Pearson r	0.91595	0.92737

In particular, Hybrid models delivered higher R^2 scores for BTC and ETH and showed better error resilience in fluctuating price conditions. RNN, although competitive in low-volatility assets like Cardano, struggled under noisy regimes.

D. Visual and ROI-Based Comparison

Visual inspections of predicted vs actual prices further confirmed the Hybrid model's superiority:

- **Bitcoin & Ethereum**: Hybrid predictions were smoother and more stable. RNNs responded faster but were prone to

JOURNAL OF EMERGING TECHNOLOGY AND DIGITAL TRANSFORMATION
ONLINE ISSN
3006-9726
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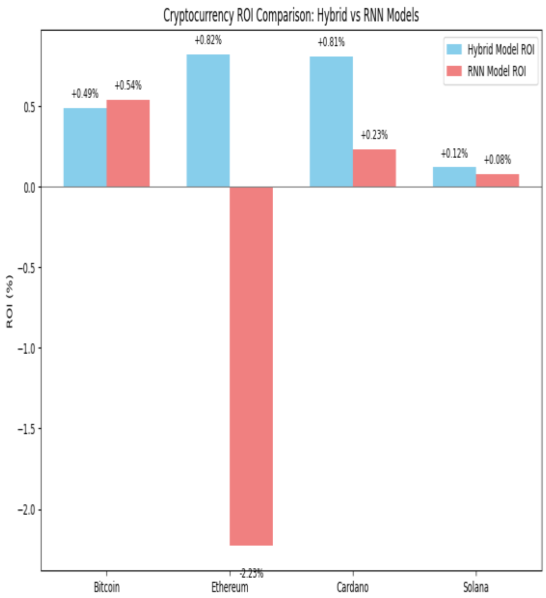
overshooting.

- **Cardano**: Both models performed closely due to the asset's narrower price band.
- **Solana**: Hybrid outperformed in trend recognition, avoiding erratic behavior during rapid shifts.



ROI Results:

Cryptocurrency	Hybrid ROI (%)	RNN ROI (%)
Bitcoin	+0.49	+0.54
Ethereum	+0.82	–2.23
Cardano	+0.81	+0.23
Solana	+0.12	+0.08

The Hybrid model consistently generated **positive ROI**, demonstrating higher financial reliability. The RNN model's predictions, although occasionally accurate, failed to deliver stability in assets like Ethereum.

E. Error Analysis and Volatility Sensitivity

1) Error Behavior

- **RNN**: High error variability, especially around trend reversals and volatile zones.
- **Hybrid**: More consistent error margins, lower sensitivity to noise, and better error distribution control.

F. Trend Reversal and Robustness

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3006-9726
PRINT ISSN
3006-9718
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Hybrid models showed a **gradual and reliable** adjustment to trend reversals, whereas RNNs responded faster but with instability. Overfitting risk was notably higher in the RNN during calm markets, while the Hybrid model preserved robust regularization.

Behavior Type	**RNN**	**Hybrid**
Error Variability	High near volatility	Moderate
Trend Reversal Response	Fast but unstable	Gradual and reliable
Overfitting Risk	Higher	Lower
Robustness	Moderate	High

G. Final Insights

The Hybrid GRU + Transformer model consistently outperformed RNN in generalization, ROI, and robustness. Its strength lies in capturing both short-term and long-term patterns, making it better suited for dynamic environments such as crypto trading.

Key Takeaways:

- **Hybrid model** offers better **trend prediction**, **stability**, and **financial ROI**.
- **RNN model** remains competitive in **stable regimes** but lacks adaptability.
- Future enhancements could involve integrating **market sentiment**, **multi-feature inputs**, or **reinforcement learning** for strategy optimization.

Conclusion and Future Work

This study introduced a real-time ROI prediction framework for cryptocurrency markets using a hybrid deep learning model that combines GRU and Transformer encoders. By leveraging live minute-level data from the CoinGecko API, the system effectively processed time-series inputs and outperformed traditional models like Vanilla RNN in metrics such as RMSE, MAE, R^2, and ROI. The hybrid model's integration of GRU’s sequential learning and the Transformer's attention mechanism enabled accurate and financially meaningful predictions, especially in volatile conditions across assets like BTC, ETH, ADA, and SOL. Beyond prediction, the framework supported ROI-based decision-making, offering practical relevance for algorithmic trading applications.

For future work, several enhancements are proposed. Model enrichment could involve deeper multi-head architectures,

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3006-9726

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reinforcement learning for strategy optimization, and uncertainty quantification through Bayesian methods. Data diversification may include sentiment analysis, technical indicators, on-chain metrics, and modeling inter-crypto relationships. Practical deployment opportunities include developing autonomous trading bots, user dashboards, and robust risk management layers. Finally, real-world validation through backtesting, paper trading, and live deployment trials will be essential to assess long-term performance and usability in dynamic market environments.

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