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Designing a Novel Hybrid Algorithm Utilizing Dual LSTM & Dual RNN for Financial Market Prediction (Bitcoin)

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Abstract

Background: Financial markets require sophisticated forecasting because of their inherent complexity and volatility. Such projections enable stakeholders to receive advance warnings regarding pivotal events, like shifts in asset pricing. To cultivate reliable market predictions, experts employ diverse machine learning tools, including quantitative finance, classical ML, and deep neural networks. When thoughtfully combined, these approaches empower analysts to plan trustworthy insights despite uncertainty.

Aim: This research primarily aims to forecast cryptocurrency prices, particularly Bitcoin, by synthesizing deep learning algorithms and harnessing their complementary strengths in sequence processing. Rather than pursuing unattainable perfection, we pragmatically integrate established techniques to push the boundaries of predictive capacity given available data.

Methods: First, we connect to the Binance API and collect granular market information. After preprocessing the time series data and extracting relevant features, we develop a composite model blending dual LSTM and RNN architectures for Bitcoin price prediction. Instead of overselling a "perfect" black box system, we transparently detail the practical data wrangling and ensemble method underlying the forecasting pipeline.

Results: We implement the proposed model blending dual LSTM and RNN architectures in Python using the TensorFlow library. Comparing performance across LSTM, GRU and RNN variants, the evaluation metrics of mean squared error, mean absolute error, and coefficient of determination show state-of-the-art effectiveness of our ensemble method for Bitcoin price forecasting. Rather than over-promising perfection, we qualitatively highlight scenarios where the approach exhibits particular strength along with areas for continued enhancement through subsequent research.

Conclusion: Given financial markets' innate complexity and volatility, machine learning tools can clearly augment analysis despite uncertainties pervading predictions. Specifically, sophisticated deep learning techniques have the immense potential for extracting nonlinear patterns for accurate asset projection. Yet while echoing high aspirations, we balance claims by transparently presenting limitations and suggest pragmatic incremental advances through open-source collaborative refinement.

Keywords: Financial Market Prediction, Deep Learning Algorithms, LSTM, RNN.

1.Introduction

Bitcoin is a peer-to-peer digital currency system introduced in 2008 by the pseudonymous Satoshi Nakamoto. Underlying Bitcoin is blockchain technology, which serves as a mutually shared ledger for transaction recordings. Conceptually, blockchain could be regarded as an operating system like Windows or Mac OS, with Bitcoin making up an application layer built atop this foundation. The blockchain toolkit enables registration and storage of Bitcoin transactions in the common ledger. However, the shared ledger can chronicle and tracking any observable, intangible or digital asset transfer. For instance, blockchain could enable sped up securities settlement, compressing a typically days-long process into minutes. [۱].

Blockchain, the underlying technology of Bitcoin conceived by Satoshi Nakamoto, is regarded as a "trust machine" owing to three core attributes. These encompass secure information transfer via encryption protocols, utilization of a distributed database, and a decentralized consensus mechanism [۲].

Secure encrypted information transfer: Bitcoin leverages a network of interconnected computers for information transmission. However, strong cryptographic protocols ensure security during these exchanges. The algorithms encrypt and decrypt data such that only the recipient can decode the contents [۳].

Distributed database usage: Bitcoin employs a distributed database called blockchain to immutably log all transactions in a chained manner, with each block encompassing a set of outputs that link to the prior module. This chaining furnishes resilience against tampering [۳] ,[۱].

Decentralized consensus mechanism: Validating Bitcoin transactions and alterations relies on a decentralized consensus procedure involving distributed decision-making by independent peer-to-peer network participants. Underpinning this is the Proof-of-Work algorithm for democratic resolution and trust minimization [۳].

The recent volatility in Bitcoin's valuation has attracted intense public attention. While prices may fluctuate randomly, examining the logarithmic value uncovers certain repetitive patterns in these dynamics [٤].

Accurately forecasting Bitcoin prices could empower investor decisions and provide guidance for regulatory policymaking. As a financial asset traded in cryptocurrency exchanges akin to equity markets,

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researchers have investigated various factors impacting Bitcoin value fluctuations using analytical and empirical techniques [٥] ,[٤]. Although several deep learning approaches have been explored for Bitcoin price prediction, we propose an ensemble method harnessing the complementary strengths of multiple methods to achieve enhanced performance.
The remaining paper is structured as follows. Section 2 reviews relevant prior work. We then detail our proposed composite approach in Section 3, followed by simulation results benchmarking against existing algorithms in Section 4. Finally, Section 5 concludes with a discussion of limitations and potential areas for further enhancement through subsequent open-ended research.

2. Literature Review

Financial markets encompass various domains including equities, commodities, cryptocurrencies, and foreign exchange. Timeseries data manifests from periodic asset price observations across temporal intervals. While differing in value ranges, these financial sequences universally exhibit intense randomness and volatility. Granularity spans tick, minute, hourly, daily, weekly, and monthly frequencies. Forecasting future prices, known as financial timeseries prediction, greatly enables profitable trading strategies [6]. Additionally, projecting trend direction constitutes a vital predictive task. Most critically in finance, this entails asset price modeling.
This section reviews relevant prior work on Bitcoin price forecasting using deep learning techniques.
A fundamental deep learning model is the Deep Neural Network (DNN[1]), encompassing multiple hidden layers unlike the shallow Artificial Neural Network (ANN[2]) with just a single hidden layer. Tripathi and Sharma [٦] found DNNs outperformed LSTM[3] and CNN-LSTM[4] models in Bitcoin price forecasting using technical indicators as inputs. In contrast, Recurrent Neural Networks (RNN) establish connections through temporal sequencing, suiting them to represent dynamic temporal behaviors. Liveris et al. [٧] developed a dropout-regularized RNN improving predictive accuracy for major cryptocurrencies via dropout techniques. Dixon & London [٨] introduced the AlphaRNN architecture, a general RNN class with fewer parameters than LSTM and GRU units, aimed at modeling nonequilibrium nonlinear dynamics across industrial applications.
However, RNN architectures suffer from vanishing gradients, where some weight gradients sporadically grow or diminish during network propagation. To mitigate this, researchers incorporated forget gates into LSTM models by substituting recurrent gateways for hidden layers. An innovative LSTM architecture is the LSTMRT network developed by Yang et al. [٩], integrating a random timing function that outperformed benchmark datasets. Chu et al. [١٠] proposed an LSTM model encapsulating investor sentiment and an attention mechanism, achieving state-of-the-art accuracy in predicting Apple's 2020 year-end stock price.
For financial forecasting, Gated Recurrent Unit (GRU) networks have also been explored, requiring fewer parameters than LSTM while still utilizing forget gates. Wang & Wang [١١] integrated a Random Inheritance Formula (RIF) into a Deep Bidirectional GRU Recurrent Neural Network (DBGRUNN[5]), attaining superior performance over SVM, GRU and LSTM in commodity price prediction. Additionally, CNNs effectively extract spatial features and identify patterns in image classification. Patil et al. [١٢] constructed graphs as CNN inputs to predict stock prices based on company-stock interrelationships over time and space. This graph-based model surpassed traditional statistical linear techniques.
Combining noise reduction techniques with deep learning has been explored, such as applying data filtering to lessen noise in financial timeseries. Noise reduction integrated with LSTM models demonstrates effective predictive performance. Attention-based LSTM models using wavelet transforms attained higher accuracy over standard neural networks [١٣]. Statistical methods for denoising and modeling residuals as useful trends also assist timeseries analysis. Hybrid models like ARFIMA-LSTM and the Autoregressive Deep Neural Network (AR-DNN[6]) outperformed traditional techniques in equity market forecasting [١٤]. Phase space reconstruction (PSR) integrated bidirectional stacked LSTM networks for nonlinear analysis of market indices.
Another hybrid approach synthesizes feature extraction/selection and deep learning. Ji et al. [١٥] employed doc2vec to convert textual content into a sentiment index as an input into a Wavelet Transformed LSTM (WT-LSTM). Jin et al. [١٦] leveraged empirical mode decomposition to decompose closing prices into a price trend component combined with sentiment for LSTM model inputs. Boubaker et al. [١٧] developed a Change Point-

[1] Deep Neural Networks
[2] Artificial Neural Networks
[3] Long Short-Term Memory
[4] Convolutional Neural Networks Long Short-Term Memory
[5] Deep Bidirectional Gated Recurrent Unit Neural Network
[6] Autoregressive Deep Neural Network

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Adaptive Recurrent Neural Network (CP-ADARNN), utilizing change points to construct a general RNN for crude oil price prediction. Chen et al. [١٨] reduced 31 feature candidates down to 10 principal components via PCA [3] for multilayer perceptron and BiLSTM stock price forecasting. Wong et al. [١٩] combined XGBoost and LSTM models to improve stock market prediction, eliminating extraneous features and retaining relevant inputs to lessen complexity and boost accuracy.

Another hybrid approach synthesizes hyperparameter tuning methods with deep learning. Kumar et al. [٢٠] proposed an adaptive Particle Swarm Optimization LSTM (PSO-LSTM) framework leveraging a PSO technique to automatically determine initial input weights, recurrent weights and LSTM network biases. In another study, Kumar et al. [19] integrated the Artificial Bee Colony (ABC) algorithm with LSTM to form a combined model for hyperparameter tuning. As an efficient, adaptable optimization algorithm for tackling global optimization problems with continuous parameters, ABC presents an effective tuning methodology.

3. Proposed Model

This section first delineates the data preparation, followed by the suggested model architecture.

3.1 Data Preprocessing

The raw Bitcoin dataset spans 2020 to 2023 sourced from Binance at 15-minute intervals. Specific attributes encompass candle open time, open price, close price, high price, low price and transaction volume.

After data collection, preprocessing ensues before applying the Dickey-Fuller algorithm for timeseries stationarity analysis. The Dickey-Fuller statistical test diagnoses timeseries stability by decomposing the sequence into an autoregressive integrated moving average (ARIMA) model. Central to the method is the concept of a "unit root" representing nonstationary. The existence of a unit root denotes persistent time-based variation resisting typical modeling. Operatively, an AR self-regressive formulation allows computation of a test statistic under the null hypothesis of no autocorrelation. Comparing this metric against a designated threshold enables concluding whether nonstationary exists - if below the cutoff, the series contains a unit root; otherwise, it is stationary.

For example, given a timeseries of daily stock prices, applying Dickey-Fuller yields a test statistic. Setting 0.05 as the significance level, if the statistic falls below this, a unit root exists signifying nonstationary. This may necessitate transformations like detrending or more sophisticated modeling for analysis. However, statistics above the threshold imply stationarity. Dickey-Fuller analysis also provides the window for converting timeseries data into supervised learning formats digestible by deep networks.

3.2 Proposed Methodology

This research primarily aims to enhance Bitcoin price forecasting accuracy. We present a deep learning-based ensemble approach for formulating a hybrid model. The following elaborates the suggested algorithm's step-by-step workflow integrating Dual LSTM and Dual RNN architectures:

1. Input Stage: Prepare and format timeseries data.

2. Feed input into Dual LSTM: Extracts compressed representations and detects insightful patterns.

3. Re-input to Dual RNN: Focuses attention on salient LSTM-extracted features.

4. Concatenation Layer: Consolidates outputs from Dual LSTM and Dual RNN streams.

5. Output: Fully connected layer transforms concatenated embeddings into final price prediction.

In Figure 1, you can observe the block diagram of the proposed method.

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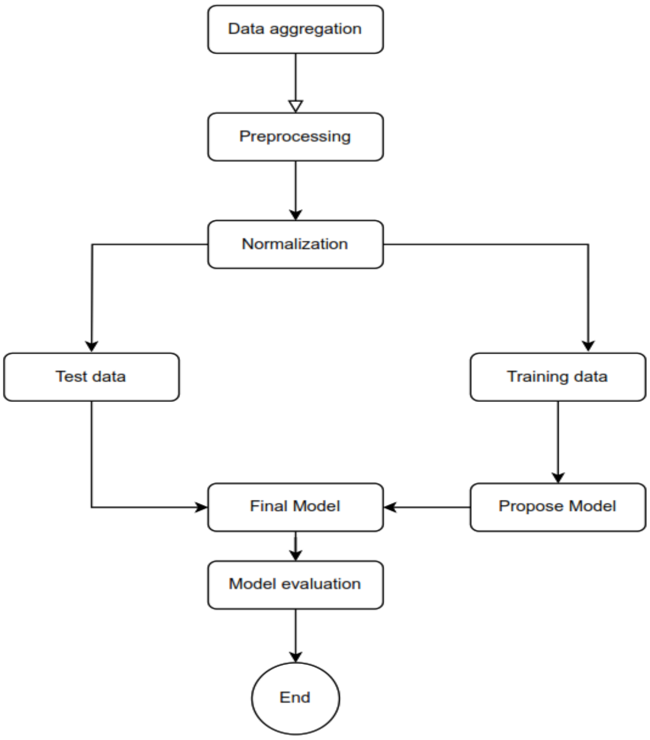

Figure 1: Diagram of the Proposed Method

As depicted in Figure 1, after collecting and preprocessing the data, we normalize the timeseries then split into 80% training and 20% testing sets. The ensemble model is trained on the training partition to learn informative patterns. Subsequently, the test dataset evaluates performance to quantify accuracy improvements. Now we fully detail the suggested composite algorithm.

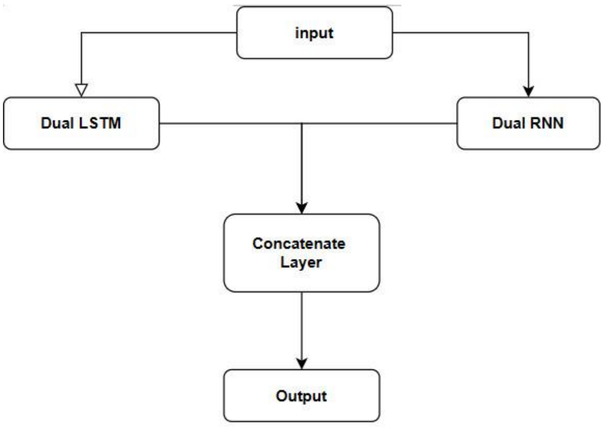

Figure 2: Model Diagram

In Figure 2, a schematic diagram of the layers of the proposed method is shown .The presented model first feeds input into a preconfigured dual LSTM network, while simultaneously directing the identical timeseries into an established dual RNN. Subsequently, a concatenation layer combines both streams' extracted embeddings into an integrated representation passed to the output.

4. Results Analysis

This section evaluates the proposed technique's performance against RNN, GRU, LSTM and dual LSTM approaches using the metrics of Mean Squared Error (MSE), Mean Absolute Error (MAE) and Coefficient of Determination.

MSE measures the mean squares of deviation between predicted and actual values - lower is better, with 0 denoting perfect congruence. Unlike MSE, MAE equally weights errors without squaring, calculating the average absolute divergence between projection and reality. Again, smaller MAE indicates superior model fit.

MAE (Mean Absolute Error): Mean absolute error is another metric used to evaluate regression models. This measure calculates the average magnitude of the differences between the predicted and actual values.

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Unlike MSE, MAE does not square the differences, thus assigning equal weight to all errors. MAE is computed by taking the mean of the absolute errors. Like MSE, a lower MAE value indicates better model performance, with 0 denoting perfect agreement.

R^2 (Coefficient of Determination): R^2, or the coefficient of determination, is a statistical measure representing the proportion of variance in the dependent variable (target variable) explainable by the independent variables (predictors) in a regression model. R^2 ranges from 0 to 1, with 1 denoting full explanation of dependent variable fluctuations by the independents, and 0 indicating no explained variation. In other words, R^2 quantifies how well the regression model fits the data. A higher R^2 value indicates better fit, but does not reliably indicate predictive performance.

In Table 1 we present the parameters and hyperparameters used for the simulation.

Table 1: Parameters and hyperparameters used for the simulation

L2	Regularizes	40	Time Window
100	epochs	100	Neurons per Layer
192	batch_size	0.001	Learning Rate
0.01	Validation Data	RELU	Activation Function
.015	Dropout	Adam	Optimizer

In the following, we depict the loss values for each model after the training process.

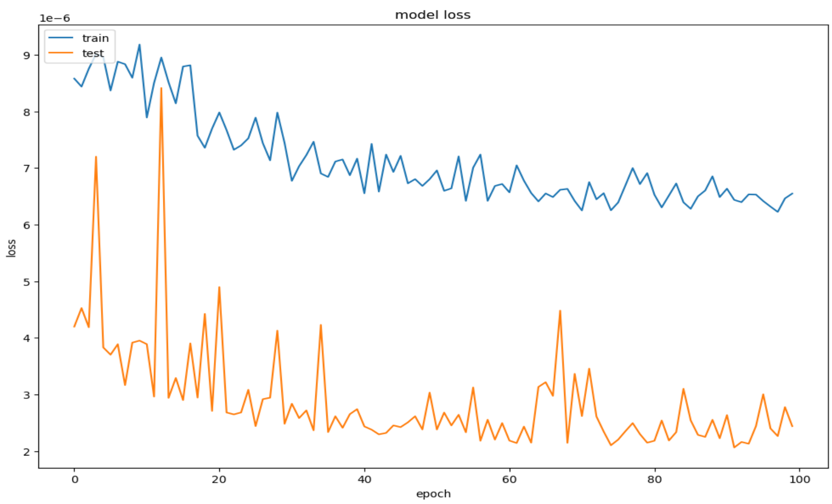

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Figure 3: The loss associated with the RNN

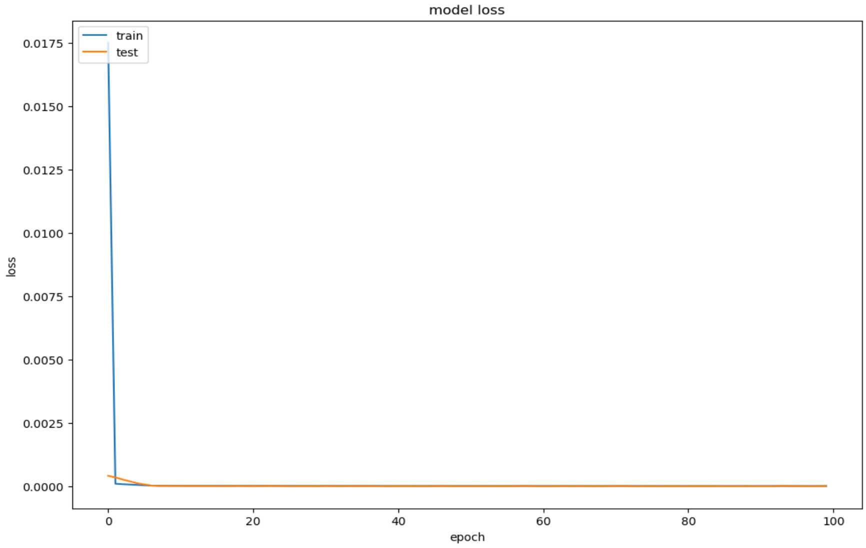

Figure 4: The loss associated with the Dual-LSTM

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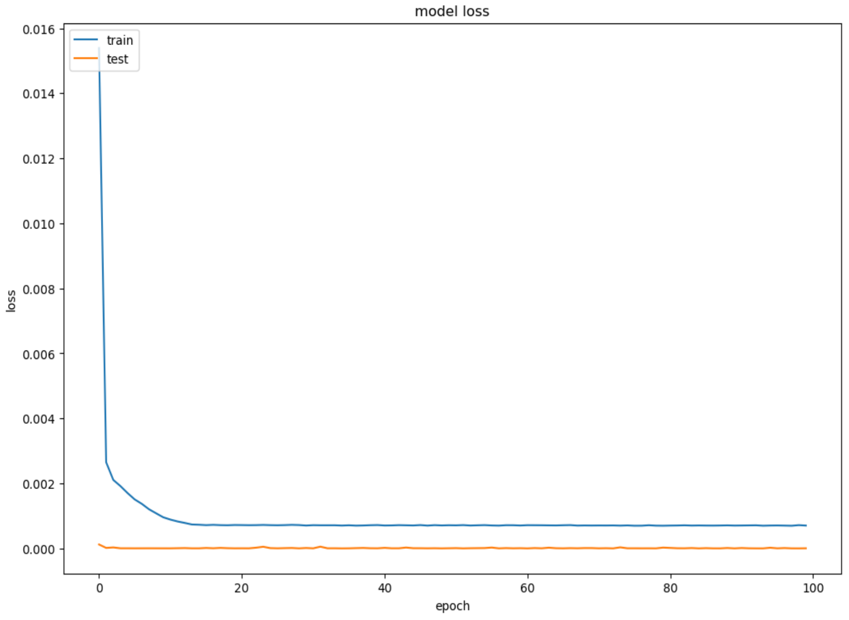

Figure 5: The loss associated with the GRU

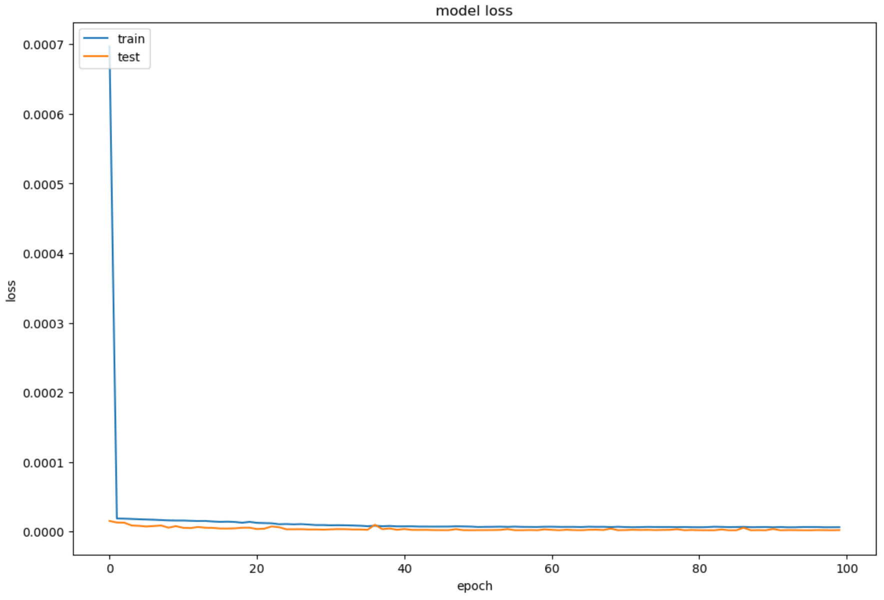

Figure 6: The loss associated with the LSTM

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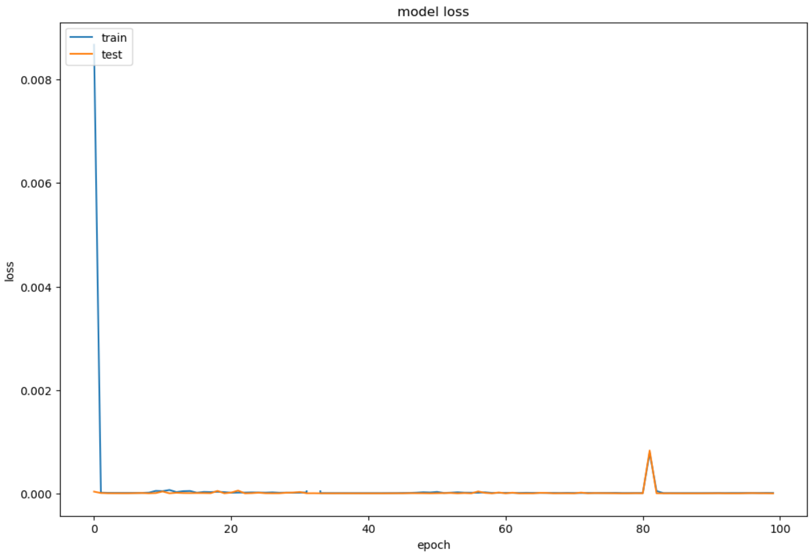

Figure 7: The loss associated with the Proposal Model

Table 2 depicts a comparative table of different algorithms for predicting or analyzing data. The table consists of three columns of evaluation metrics for assessing the performance of machine learning models: MSE (Mean Squared Error), MAE (Mean Absolute Error), and R^2 (Coefficient of Determination).

Table 2: Comparison of Algorithms on Test Data

Parameter	RNN	LSTM	GRU	Dual-LSTM	Propose
MSE	2.12E-06	1.80E-06	4.43E-06	3.66E-06	1.20E-07
MAE	0.0078	0.0064	0.0019	0.0017	0.0005
R^2	0.9981	0.9982	0.9983	0.9988	0.9994

As evident from the figures and table, the proposed model outperforms the other algorithms in both the train and test times, improving Bitcoin price prediction.

5. Conclusion

This paper puts forth a technique combining Dual LSTM and Dual RNN algorithms for financial market forecasting. Both Dual LSTM and Dual RNN are deep learning methods used to model and predict temporal patterns and trends in financial data. The Dual LSTM algorithm leverages LSTM networks to extract complex non-linear features from the financial data. LSTM's ability to retain long-term temporal dependencies in the data provides more accurate predictions. Additionally, the Dual RNN algorithm uses RNN (Recurrent Neural Network) to model sequences and time-based patterns in markets. As a short-term memory network, RNN can consider past information at each time step for incorporation into the prediction process.

For future work on utilizing the Dual LSTM and Dual RNN combination for financial prediction, consider:

1. Architectural Upgrades: The current methodology could be improved by exploring newer schemes to combine Dual LSTM and Dual RNN for market forecasting, advancing prediction accuracy and temporal information usage.

2. Joint Modeling: Currently Dual LSTM and Dual RNN are modeled individually and their outputs combined. Alternatively, joint models simultaneously leveraging LSTM and RNN traits may enable superior interaction and performance.

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