Navigating XRP Volatility: A Deep Learning Perspective on Technical Indicators

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***Abstract*—The rise of cryptocurrency has dramatically changed. Cryptocurrencies have dramatically reshaped the landscape of financial transactions, enabling seamless cross-border exchanges without centralized oversight. This revolutionary shift, powered by blockchain technology, has democratized currency control, entrusting it to a widespread network of participants rather than a single entity. Originating from Satoshi Nakamoto's introduction of Bitcoin, this digital currency model operates on a decentralized framework, contrasting starkly with traditional, centrally governed monetary systems. This research delves into forecasting the price of Ripple (XRP) by leveraging advanced deep-learning approaches and various technical indicators. This study achieves remarkable precision in its predictions through the meticulous preprocessing of data and the application of neural networks, particularly the convolutional neural network-gated recurrent unit hybrid model. Technical indicators further refined these forecasts, highlighting the effective collaboration between machine learning techniques and financial market analysis. Despite the volatile nature of the cryptocurrency market, this work makes a substantial contribution to the field of cryptocurrency prediction strategies, advocating for further investigations into the effects of macroeconomic factors and the utilization of more extensive datasets to deepen our understanding of market dynamics.**

Keywords*—Cryptocurrency; ripple; convolutional neural network; gated recurrent unit; technical indicators

I. Introduction

Cryptocurrency has witnessed massive followings recently, making it popular and facilitating hassle-free cross-border transactions. It has given a new dimension to exchanging digital assets that run over Blockchain technology. This is a decentralized currency, meaning no one controls it; it is community-driven. Satoshi Nakamoto first coined this concept, leading to the development of 'Bitcoin' [1]. Unlike a centralized currency with control vested in a central authority like a government, a kingdom, or an organization, cryptocurrencies operate and are maintained by a distributed network system commonly known as nodes using blockchain technology [2].

The price of a centralized currency vis a vis another currency widely depends on the demand-supply dynamics and printing of currency. The central agency can print more currency anytime, which impacts a currency's face value. On the other hand, in the case of cryptocurrency, the supply is predetermined and transparent. Thus, the value of cryptocurrencies is more directly influenced by Demand-supply dynamics. Because of these features, investors tend to invest in cryptocurrency and to minimize investment risks, they use various mathematical models to forecast future prices. Cryptocurrencies claimed a market valuation of more than USD 2.3 trillion as of April 2021[4].

Ripple is the fastest-growing currency in recent times, demanding continuous forecasting because of its volatility in pricing [3]. In this paper, we have used Technical Indicators to predict the price of Ripple (XRP) coins using deep learning techniques. Technical Indicators are used mainly to know the price movement of a currency, i.e., whether it will rise or go down with passing time.

The perspective of this paper is to address the challenges of predicting the price of Ripple (XRP) by utilizing deep learning techniques. As deep learning is one of the subsets of AI (Artificial Intelligence), it has ensured the detection of complex patterns in large datasets, proving itself as more favorable for forecasting in highly volatile markets. Technical Indicators are also used to provide insights into price movements; the research aims to improve the accuracy of predictions. Hence, it offers investors a more reliable tool in the course of decision-making.

This research has great relevance as it has the potential to improve the predictability and stability of investments made in Ripple. The process of precise prediction algorithms can help investors in decision-making and improved risk management, which will support the general development and steadiness of the Bitcoin market. Going further, the impact of this research can be enlarged by applying the proposed approaches to additional cryptocurrencies. This research work focuses on using technical indicators and deep learning to create an authentic Ripple (XRP) prediction model. This study adds to the expanding body of knowledge in forecasting cryptocurrencies by dealing with the related problems of price volatility and the accuracy of prediction. This is also helpful in offering useful guidance for investors in navigating this continuously changing market.

This paper helps in surveying the ongoing state of cryptocurrencies, focusing on Ripple's (XRP) ascent and economic relevance. It spells out the process for forecasting

Ripple's price changes using the methods of deep learning as well as technical indicators. The accuracy and efficacy of these predictive algorithms are indicated by examining the output. The study also directs the ramifications of the outcomes, the difficulties encountered, and potential avenues for further investigation. The findings and significance of this research for Bitcoin investments are summed up in the conclusion.

II. Background

A. Ripple (XRP)

Ripple (XRP), developed by Ripple Labs Inc. co-founders Chris Larsen and Jed McCaleb, and diverges from traditional cryptocurrencies as a digital payment protocol. Operating on a decentralized blockchain, it prioritizes facilitating secure, instant, and low-cost cross-border transactions. Notably, XRP's role as a bridge currency streamlines the exchange of fiat currencies internationally, prompting its adoption by many global banks for transactions and presenting investment potential for investors [5].

B. Technical Indicators

- Technical indicators track market price movements, assisting investors in timing their investments [6]. This study integrates such indicators into the dataset, categorized as Technical Indicator-1 to Technical Indicator-4. Through feature selection, specific indicators from each group were chosen for predictive analysis.

- Relative Strength Index (RSI) was developed by J. Welles Wilder. As a financial market technical indicator. The RSI measured the speed and change of price movement using a momentum oscillator as per Eq. (1).

$$RSI = 100 - \left[\frac{100}{1+\frac{Average\ gain}{Average\ Loss}}\right] \quad (1)$$

The RSI is calculated mostly for a period of 14 days.

- The Stochastic Indicator detects potential trend reversals, indicating oversold conditions within a 0 to 100 range on two axes, by comparing current prices with historical highs and lows [6]. Eq. (2) and Eq. (3) outline the calculation process, aiding in its interpretation.: -

$$K\% = ((A-B)/(C-B)) * 100 \quad (2)$$

$$D\% = X - period\ simple\ moving\ average\ of\ K\% \quad (3)$$

The indicator uses 14 days to calculate $\%D\ and\ \%K$. The user can also change the period as per the requirement [8].

where,

A: $Current\ Close$

B: $Lowest\ Low\ in\ X\ Period$

C: $Highest\ High\ in\ X\ period$

X: $14\ days\ period$

- The Commodity Channel Index (CCI) gauges price variance from the average over a specified period, with values above 100 indicating a strong uptrend and those below -100 signalling a downtrend:

$$CCI = \frac{TP-MA}{.015*Mean\ Deviation} \quad (4)$$

Where,

$$Typical\ Price(TP) = \sum_{i=1}^{P} \frac{(High + low + Close)}{3}$$

$$P: Number\ of\ Periods$$

$$Moving\ Average\ (MA) = \frac{\sum_{i=1}^{P}(Typical\ price)}{P}$$

$$Mean\ Deviation\ \frac{\sum_{i=1}^{P}(TP-MA)}{P}$$

- The Moving average convergence/divergence (MACD) is a momentum oscillator used for trade trends but not to identify the oversold or overbought conditions [5]. Eq. $(5)\ and\ Eq.(6)$ shows the calculation of MACD [3]: -

$$MACD_P = EMA_{12}(p) - EMA_{26}(p) \quad (5)$$

$$S_{MACD} = EMA_9(MACD) \quad (6)$$

Where,

$$EMA_{12}(p) = 12 - Peroid\ Exponential\ Moving\ Average\ Price$$

$$EMA_{26}(p) = 26 - Period\ Exponential\ Moving\ Average\ Price$$

$$EMA_9 = 9 - Period\ Exponential\ Moving\ Average\ Price$$

- The Money Flow Index (MFI) is an oscillator that combines price and volume data to evaluate strength and momentum on a scale of 0 to 100, with readings above 70 indicating overbought conditions and below 30 indicating oversold conditions, potentially signalling a forthcoming price rebound opportunity [6].

$$MFI = 100 - \frac{100}{(1+Money\ Ratio)} \quad (7)$$

Where,

$$Money\ Ratio = \frac{14\ period\ positive\ money\ flow}{14\ period\ negetive\ money\ flow}$$

- The Chikou Span, or the Lagging Span or Lagging Line, is one of the five lines comprising the Ichimoku Kinko Hyo indicator.

$$CS = Last\ Close\ Price\ Plotted\ 26 - Periods\ in\ Past \quad (8)$$

Where,

$$CS: Chikou\ Span$$

- The “Williams %R (Williams Percentage Range” is a financial tool that measures the oscillation in the price range for any financial asset and in our case the price of the cryptocurrency. It is based on the volume of purchase and sales of an asset and plays an important role for trading decisions.

$$Williams\ \%R = \frac{Highest\ High - Current\ Close}{Highest\ High - Lowest\ Low} \quad (9)$$

where,

$$Highest\ High: Highest\ price\ in\ the\ lookback\ period\ \ 14\ days$$

$$Lowest\ Low: Lowest\ price\ in\ the\ lookback\ period\ 14\ days$$

- The Normalized Average True Range (NATR) is similar to the Average True Range (ATR) indicator, but it has an extra step. The NATR takes the ATR values and adjusts them to fit on a scale from 0 to 100. This makes it easier to compare the volatility of different assets
  - The Average Directional Index (ADX) measures how strong a market trend is by comparing two other indicators: the Positive Directional Index (+DI) and the Negative Directional Index (-DI). It helps traders see how much momentum a trend has and spot good trading opportunities. A high ADX means a strong trend, while a low ADX means the market is not trending much, which helps traders decide when to trade and manage their risk
  - The On-Balance Volume (OBV), attributed to Joseph Granville, evaluates cumulative volume flow in financial instruments like stocks, currencies, or commodities. It assists traders and investors in spotting potential price trends and reversals by analyzing the relationship between price movements and trading volume [3].
  - Triple Exponential Moving Average (TEMA) is a variation of the traditional Exponential Moving Average (EMA), with the key difference being that TEMA incorporates triple smoothing, making it more responsive to recent price movements. Eq. (10) indicates the calculation of TEMA.

$$TEMA \ = [(3 \times EMA_1) - (3 \times EMA_2)] + EMA_3 \quad (10)$$

Where,

$$EMA_1: Exponential\ Moving\ Average\ (EMA)$$

$$EMA_2: EMA\ of\ EMA_1$$

$$EMA_3: EMA\ of\ EMA_2$$

III. Literature Review

Athey, Parashkevov, et al. [8] create a pricing model for Bitcoin and offer conflicting data about the model's capacity to explain price movements. Using an equilibrium model, Pagnotta and Buraschi [9] examine the value of Bitcoin and other decentralized network assets. Raskin and Yermack [10], for instance, analyze the consequences of central banking. The subject of Yermack is corporate governance. Huberman, Leshno, et al. [11] examine the cost of mining bitcoin. Harvey [12] concludes with a thorough explanation of the workings of cryptocurrency. Chan and Bessembinder [13] and, LeBaron Sullivan [14], Timmermann and White [15] concentrate on how profitable these tactics are in equities markets. Based on particular stock portfolios, Han, Yang, and Zhou [16] and Shynkevich [17] compare a few particular MA strategies with the buy-and-hold approach. Neely, Rapach, Tu, and Zhou [18] use technical indicators to predict the premium for stock risk. Huang and Huang [19] use stock exchange-traded funds (ETFs) to evaluate MV methods. For instance, Allen and Karjalainen (2018), Brown, Goetzmann, and Kumar [20], Lo, Mamaysky, and Wang [21], and Hsu, Hsu, and Kumar [22], among others, also examine additional technical trading principles in addition to MV techniques. Furthermore, Hsu, Taylor, and Wang [23] use foreign exchange data to evaluate a set of technical analysis methods.

To comprehend the dynamics of crypto asset prices and, more specifically, how price information is transmitted between Bitcoin markets and traditional ones, Giudici and Polinesi [24] applied hierarchical clustering to Bitcoin prices collected from various exchanges. Akyildirim, Goncu, and Sensoy [25] examined the prediction of twelve cryptocurrencies at the daily and minute frequency levels using machine learning classification techniques. It has been demonstrated through social media interaction analysis that sentiment indexes may be used to forecast price bubbles (Chen & Hafner [26]) and that sentiment gleaned from Reddit subject conversations correlates with prices (Phillips and Gorse [27]). The use of optimized deep learning algorithms with improved classification results over earlier research (Bartolucci et al., [28]; Uras and Ortu [29]) is a significant addition to this work.

IV. Feature Selection Method

A. Information Value (IV)

Regression analysis heavily relies on feature selection to improve the model's performance; this finds the most essential attributes. Although the Information Value (IV) cutoff approach is generally intended for use in classification issues, we have employed it in this instance indirectly. Continuous forecasting is a technique used in time series prediction to improve model performance by removing unnecessary features. When creating a model, features with IV values higher than a predetermined cutoff are kept, whereas features with values lower than the cutoff are removed, exceeding the IV threshold ensures the maximum feasible feature relevance and model. By determining the proper IV threshold, the feature selection procedure increases the interpretability of the model and boosts predictive performance.

B. Data description

The XRP dataset, obtained from Kaggle.com, covers data from August 5, 2013, to July 6, 2021, encompassing open, close, high, and low attributes. After preprocessing, it contains 2893 observations. The dataset is partitioned into three subsets: an initial set of 202 observations for technical indicator initialization, a training set of 1924 observations, and a test set of 767 observations [7]. XRP price was low before 2017, and the return is not relatively volatile.

V. METHODOLOGY

A. Deep Learning Algorithms (DL)

The section elucidates the employment of Deep Learning (DL) algorithms, utilizing the Keras Framework for Deep Learning (Chollet et al., 2015), primarily for time series forecasting. DL architectures, characterized by multilevel complexity, encompass various models for inference. Technical Indicators with cutoff values ranging from 0.1 to 0.5 are integrated into XRP data, enhancing forecasting accuracy via deep learning methodologies.

B. Long Short-Term Memory

Recurrent neural networks (RNN) face challenges with the vanishing gradient problem, hindering their ability to learn long-range dependencies in sequential data due to diminished gradients [30]. In 1997, Sepp Hochreiter and Jurgen Schmidhuber introduced LSTM networks, equipped with specialized memory cells that enable long-term information retention, overcoming the limitations of traditional RNNs. LSTM contains a Cell State that stores long-term memory; the Hidden State captures short-term memory in LSTM networks, with Input, Forget, and Output Gates controlling information flow.

We computed some basic parameters of LSTM followed by Eq. (11) - Eq. (16)

$$f_t = \sigma(y_t + i_{t-1})X_i \tag{11}$$

$$g_t = \sigma\left(y_t W_f + i_{t-1}X_f\right) \tag{12}$$

$$p_t = \sigma(y_t W_o + i_{t-1}X_o) \tag{13}$$

$$\check{C}_t = tanh\left(y_t W_g + i_{t-1}X_g\right) \tag{14}$$

$$C_t = \sigma\left(g_t \times C_{t-1} + j_t \times \check{C}_t\right) \tag{15}$$

$$i_t = tanh(C_t) \times O_t \tag{16}$$

where, y_t is input, i_{t-1} is the output of the previous cell state, C_{t-1} is cell memory of previous LSTM, i_t is current output, C_t is the current cell state and $X, and\ W$ are the weights.

C. Gated Recurrent Unit

The Gated Recurrent Unit (GRU), an RNN variant developed by Cho et al., mitigates shortcomings of traditional RNNs via a gating mechanism facilitating information flow between network layers. It features two gates [33]: the Reset gate, which discards past information based on the previous hidden state and current input, and the Update gate, blending previous and new states. GRU's architecture excels in capturing sequential data relationships and finding applications in natural language processing, speech recognition, and time series analysis. Despite its simpler design compared to LSTM networks, GRU maintains strong performance while offering reduced computational overhead.

D. Convolution Neural Network

Convolution Neural Network (CNN) is a deep learning model. 1D Convolutional Neural Network (1D CNN) is a neural network architecture designed to process one-dimensional data sequences. 1D CNNs are used for sequence data represented along a single dimension, such as time series data or text. In this paper, we have used 1D CNN for our time series data analysis. In CNN, there is a convolution layer, which is important [31]. This layer performs the convolution operation and helps the network learn hierarchical features in the input sequence [32].

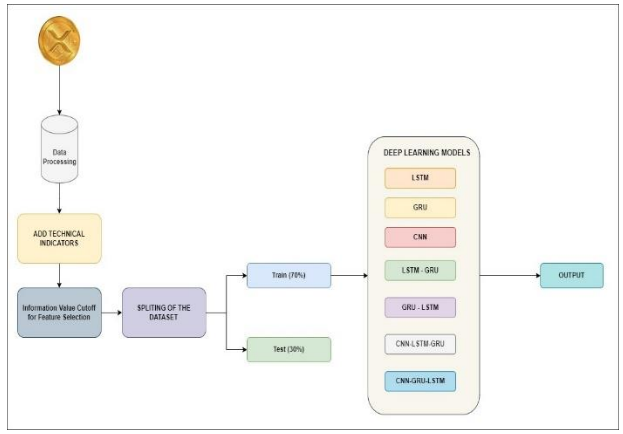


Fig. 1. Flow diagram of the proposed model.

VI. PROPOSED ENSEMBLE MODELS

In this section, we discuss our proposed ensembled models where the XRP price is combined with the technical indicators to predict the future. As shown in Fig. 1, the proposed workflows depict the first step of the data preprocessing. Second step, technical indicators are used, increasing the data set's features. In third stage, a feature selection method known as Information Value Cutoff is used with different values for different indicators, and finally, the features undergo the existing and proposed deep learning models to get the output. The proposed deep learning models are CNN-LSTM, CNN GRU, CNN-LSTM-GRU and CNN-GRU-LSTM. The ensemble model is a hybrid model that integrates CNN-LSTM, CNN-GRU, CNN-LSTM-GRU, and CNN-GRU-LSTM, whose performance is enhanced by the Attention mechanism. The model begins with a Convo 1D layer, which is used for feature extraction from the input sequence using the convolutional operations. Then, two subsequent LSTM and two subsequent GRU layers were used in the model with 64 neurons to capture the dependencies of sequential data. The model is followed by a dropout rate of 0.1 to mitigate the overfitting concerns [32]. Our model stands out because it uses an attention module that zooms in on the important parts of the input data. This makes the model more accurate. We also use a Rectified Linear Unit (ReLU) activation function to boost performance. Finally, the model flattens the data into a one-dimensional form and uses a dense layer to make predictions.

The dynamic feature of our combined models lies in the attention mechanism. This tool improves accuracy, efficiency, and clarity in deep learning models. Just like how humans focus on important details, attention helps models concentrate on key parts of the input data when making predictions. It assigns different weights to parts of the input, allowing the model to prioritize important information and ignore unnecessary details. This results in more accurate and context-aware predictions.

The flexibility and power of attention mechanisms are essential for achieving top performance in modern deep learning models.

VII. Performance Evaluation

A dataset often has messy data with missing or repeated values, so we need to clean it before using it in models. Hence, Data preprocessing is very important and involves several steps to make sure the data is ready and good for analysis. For time series data, which has its own challenges like irregular timestamps and seasonal trends, the process starts with data cleaning. This means finding and fixing missing data and removing duplicates. Next, we transform the data to make it easier to analyze, which includes scaling and normalizing it. Then, we do feature engineering, which means creating new useful features from the existing data to improve the model. We also reduce the number of features and select the most important ones for better predictions. After that, we split the data into training, testing, and validation sets. This step is crucial because it helps us accurately evaluate the model's performance and prevent overfitting.

Handling data correctly is key to making accurate, understandable, and reliable machine learning models. Properly prepared data leads to better analysis and successful machine learning tasks.

VIII. Evaluation Matrix

A. Root Mean Square Error

Root Mean Square Error (RMSE) is an important measure in regression analysis and machine learning that shows how accurate predictions are. It does this by calculating the square root of the average of the squared differences between the predicted and actual values. A lower RMSE means the model is performing better because it indicates smaller differences between the predictions and the actual results.

B. Mean Absolute Percentage Error

Mean Absolute Percentage Error (MAPE) measures how accurate forecasts are by averaging the percentage differences between predicted and actual values. It's easy to understand for everyone, not just technical experts. However, MAPE can be affected by very large errors and doesn't work well when actual values are zero [31].

C. R-Square

R-squared (R^2) measures how much of the variation in the outcome can be explained by the regression model. It helps us understand how well the model fits the data and how good it is at making predictions. The R^2 value ranges from 0 to 1:

- An R^2 of 0 means the model doesn't explain any of the variations.
- An R^2 of 1 means the model perfectly explains all the variations.

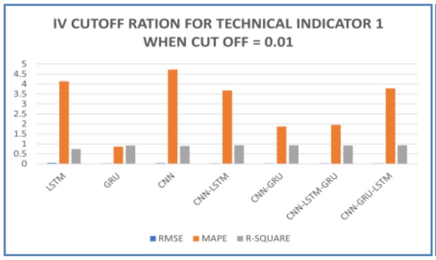
IX. Result Analysis

In this segment, we present the outcomes of simulations aimed at forecasting the price of Ripple (XRP) over the next 10 days, utilizing four technical indicators. The result shows the value of feature selection method IV with cutoff values $0.01, 0.02, 0.03, 0.04$ *and* 0.05. The forecasting dataset for XRP prices differs from the training data, allowing an accurate assessment of model performance. Various evaluation metrics, including RMSE, MAPE, and R^2, was analyzed for LSTM, GRU, CNN, and ensemble models (such as CNN-LSTM, CNN-GRU, CNN-LSTM-GRU, and CNN-GRU-LSTM hybrids), with comparative results presented in Tables I, II, III, IV. The study aims to determine the most effective model for predicting XRP prices.

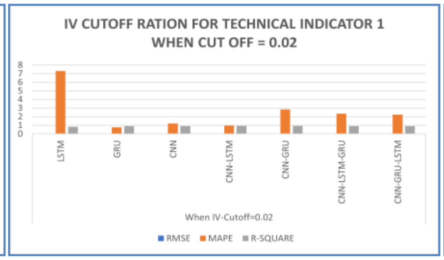
TABLE I. Normalized Values for Technical Indicator-1

		EXISTING MODELS			***PROPOSED ENSEMBLED MODELS***			
When IV-Cutoff=0.01	**MODELS**	LSTM	GRU	CNN	CNN-LSTM	CNN-GRU	CNN-LSTM-GRU	CNN-GRU-LSTM
	RMSE	0.0523	0.0301	0.0340	0.0274	0.0262	0.0295	0.0277
	MAPE	4.1404	0.8646	4.7267	3.6804	1.8724	1.9506	3.7855
	R^2	0.7371	0.9127	0.8890	0.9277	0.9343	0.9165	0.9264
		EXISTING MODELS			***PROPOSED ENSEMBLED MODELS***			
When IV-Cutoff=0.02	**MODELS**	LSTM	GRU	CNN	CNN-LSTM	CNN-GRU	CNN-LSTM-GRU	CNN-GRU-LSTM
	RMSE	0.0430	0.0319	0.0298	0.0293	0.0254	0.0297	0.0319
	MAPE	7.3072	0.7574	1.2095	0.9582	2.8467	2.3445	2.2480
	R^2	0.8220	0.9022	0.9145	0.9174	0.9382	0.9156	0.9024
		EXISTING MODELS			***PROPOSED ENSEMBLED MODELS***			
When IV-Cutoff=0.03	**MODELS**	LSTM	GRU	CNN	CNN-LSTM	CNN-GRU	CNN-LSTM-GRU	CNN-GRU-LSTM
	RMSE	0.0501	0.0298	0.0315	0.0271	0.0256	0.0308	0.0286
	MAPE	1.0798	0.5779	1.8525	1.8745	1.8732	1.8560	1.6101
	R^2	0.7587	0.9147	0.9048	0.9297	0.9369	0.9089	0.9213
		EXISTING MODELS			***PROPOSED ENSEMBLED MODELS***			
When IV-Cutoff=0.04	**MODELS**	LSTM	GRU	CNN	CNN-LSTM	CNN-GRU	CNN-LSTM-GRU	CNN-GRU-LSTM
	RMSE	0.0418	0.0316	0.0293	0.0293	0.0227	0.0304	0.0278
	MAPE	7.0830	0.5765	1.4572	0.9380	2.7703	2.8315	1.9364
	R^2	0.8320	0.9042	0.9140	0.9174	0.9504	0.9113	0.9259

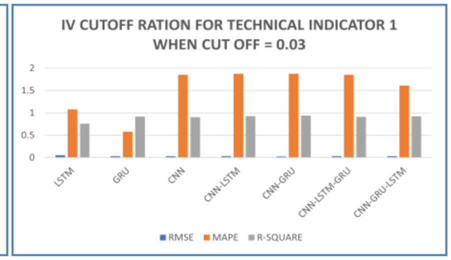
	EXISTING MODELS				*PROPOSED ENSEMBLED MODELS*			
When IV-Cutoff=0.05	**MODELS**	LSTM	GRU	CNN	CNN-LSTM	CNN-GRU	CNN-LSTM-GRU	CNN-GRU-LSTM
	RMSE	0.0415	0.0277	0.0280	0.0302	0.0256	0.0297	0.0301
	MAPE	3.9683	0.5423	1.4667	0.9477	0.6989	1.4186	3.5558
	$\boldsymbol{R^2}$	0.8342	0.9261	0.9246	0.9127	0.9369	0.9151	0.9128



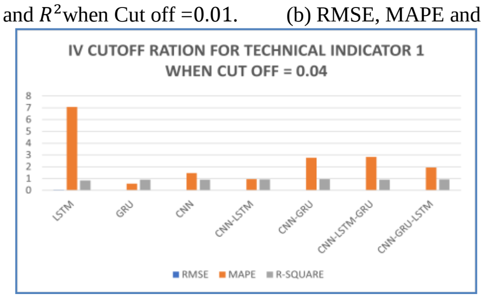
(a) RMSE, MAPE and $R^2$when Cut off =0.01.



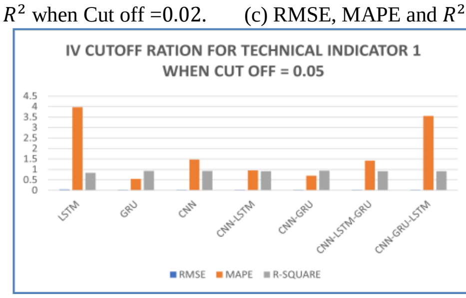
(b) RMSE, MAPE and R^2 when Cut off =0.02.



(c) RMSE, MAPE and R^2 when Cut off =0.03.



(d) RMSE, MAPE and R^2 when Cut off =0.04.



(e) RMSE, MAPE and R^2 when Cut off =0.05.

Fig. 2. Comparison of RMSE, MAPE and R^2 of existing and proposed models for technical indicator 1.

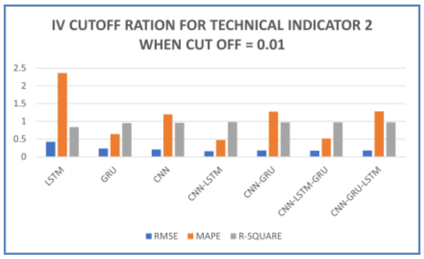
RMSE is a metric comparing predicted and actual coin prices, where lower values indicate better model accuracy. Table I showcases results from seven deep-learning algorithms across five IV-Cutoff levels, predicting prices over a 10-day span. The CNN-GRU hybrid model consistently outshines others, displaying superior performance across all IV-Cutoff values for Technical Indicator-1. These findings are further illustrated in Fig. 2(a), (b), (c), (d), and (e), presenting comprehensive data visualization. The R^2 values also affirm the model's fit, demonstrating high coefficients across various IV-Cutoff levels. The study highlights the CNN-GRU hybrid model's efficacy in predicting coin prices using Technical Indicator-1.

Table II summarizes the performance of seven deep learning algorithms applied to Technical Indicator 2 across five IV-Cutoff values for forecasting the next 10 days. Notably, the CNN-GRU hybrid model demonstrates superior performance at IV-Cutoffs 0.03 and 0.04, with RMSE values of 0.1539 and 0.1612, respectively. Conversely, CNN-LSTM-GRU exhibits better results at IV-Cutoffs 0.02 and 0.05, showcasing lower RMSE values of 0.1595 and 0.1613. CNN-LSTM stands out at IV-Cutoff 0.01, boasting an RMSE of 0.1607. R^2 values indicate robust data fit, with the highest achieved at IV-Cutoff 0.03 (0.9789). Fig. 3 illustrates these results comprehensively, depicting all values for each IV-Cutoff."

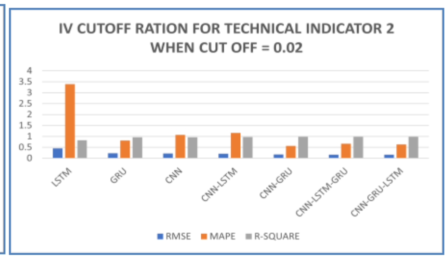
TABLE II. NORMALIZED VALUES TECHNICAL INDICATOR 2

	EXISTING MODELS				*PROPOSED ENSEMBLED MODELS*			
When IV-Cutoff=0.01	**MODELS**	LSTM	GRU	CNN	CNN-LSTM	CNN-GRU	CNN-LSTM-GRU	CNN-GRU-LSTM
	RMSE	0.4242	0.2393	0.2064	0.1607	0.1825	0.1734	0.1776
	MAPE	2.3616	0.6452	1.1983	0.4731	1.2763	0.5170	1.2806
	$\boldsymbol{R^2}$	0.8396	0.9490	0.9620	0.9770	0.9703	0.9732	0.9719
	EXISTING MODELS				*PROPOSED ENSEMBLED MODELS*			
When IV-Cutoff=0.02	**MODELS**	LSTM	GRU	CNN	CNN-LSTM	CNN-GRU	CNN-LSTM-GRU	CNN-GRU-LSTM
	RMSE	0.4513	0.2227	0.2204	0.2005	0.1662	0.1595	0.1614
	MAPE	3.3980	0.8098	1.0700	1.1617	0.5700	0.6711	0.6283
	$\boldsymbol{R^2}$	0.8184	0.9558	0.9567	0.9642	0.9754	0.9773	0.9768
	EXISTING MODELS				*PROPOSED ENSEMBLED MODELS*			
When IV-Cutoff=0.03	**MODELS**	LSTM	GRU	CNN	CNN-LSTM	CNN-GRU	CNN-LSTM-GRU	CNN-GRU-LSTM
	RMSE	0.5718	0.2140	0.2868	0.1960	0.1539	0.1754	0.1823
	MAPE	5.1379	1.1808	1.6387	0.7837	0.7666	0.7778	1.0016
	$\boldsymbol{R^2}$	0.7085	0.9592	0.9267	0.9658	0.9789	0.9726	0.9704

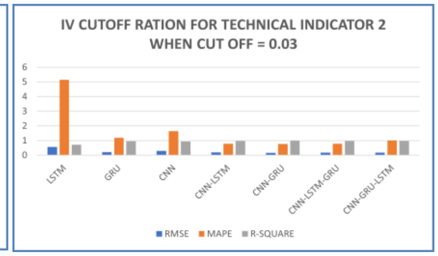
		EXISTING MODELS			*PROPOSED ENSEMBLED MODELS*			
When IV-Cutoff=0.04	**MODELS**	LSTM	GRU	CNN	CNN-LSTM	CNN-GRU	CNN-LSTM-GRU	CNN-GRU-LSTM
	RMSE	0.5006	0.2246	0.3203	0.2198	0.1612	0.1968	0.1710
	MAPE	3.6101	1.4830	2.2568	0.5316	0.5608	0.5635	0.9440
	$\boldsymbol{R^2}$	0.7766	0.9550	0.9085	0.9569	0.9768	0.9655	0.9739
		EXISTING MODELS			*PROPOSED ENSEMBLED MODELS*			
When IV-Cutoff=0.05	**MODELS**	LSTM	GRU	CNN	CNN-LSTM	CNN-GRU	CNN-LSTM-GRU	CNN-GRU-LSTM
	RMSE	0.4825	0.2534	0.2482	0.2271	0.1878	0.1613	0.1788
	MAPE	2.7127	1.9540	0.9781	1.0408	0.6091	0.3922	1.1926
	$\boldsymbol{R^2}$	0.7924	0.9428	0.9451	0.9540	0.9686	0.9768	0.9715



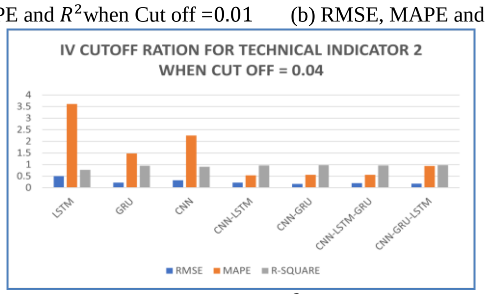
(a) RMSE, MAPE and $R^2$when Cut off =0.01



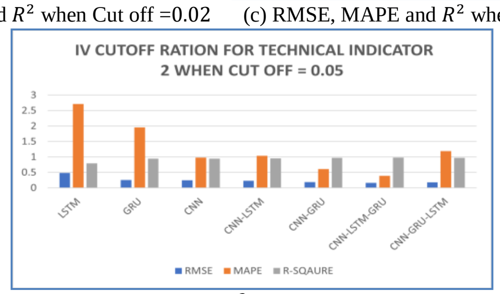
(b) RMSE, MAPE and R^2 when Cut off =0.02



(c) RMSE, MAPE and R^2 when Cut off =0.03



(d) RMSE, MAPE and R^2 when Cut off =0.04



(e) RMSE, MAPE and R^2 when Cut off =0.05

Fig. 3. Comparison of RMSE, MAPE and R^2 of existing and proposed models for technical indicator 2.

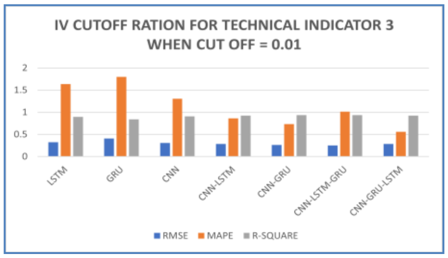
Table III shows Various deep learning algorithms were assessed for a technical indicator 3, across different threshold values. The CNN-LSTM-GRU hybrid model excelled with an IV-Cutoff of 0.01, yielding an RMSE of 0.2534 and an R^2 of 0.9379. Conversely, CNN-GRU performed better with IV-Cutoff values of 0.02, 0.03, and 0.05, showcasing RMSEs of 0.2116, 0.2359, and 0.2088, respectively, with corresponding R^2 values. CNN-GRU-LSTM outshone others with an IV-Cutoff of 0.04, achieving an RMSE of 0.2185 and an $R^2$of 0.9583. Fig. 4 (a), (b), (c), (d), (e) illustrate these results comprehensively.

Table IV shows the result obtained using seven deep learning algorithms for technical indicator 4 with five different values for the next 10 days. In technical indicator 4 result varies when the threshold value is changed. The CNN-GRU hybrid model gives better results for all the IV-Cutoff values followed by RMSE 0.2630,0.2489,0.2427,0.2517 and 0.2523. R^2 signifies the better fit of the data. In IV-Cutoff 0.01 the R^2 is 0.9331, in 0.02 R^2 is 0.9401, in 0.03 R^2 is 0.9540, in 0.04 R^2 is 0.9388 and in 0.05 R^2 is 0.9485. In Fig. 5 (a), (b), (c), (d), (e) all the values are depicted. The result shows CNN-GRU hybrid model gives better results for all the IV-Cutoff values.

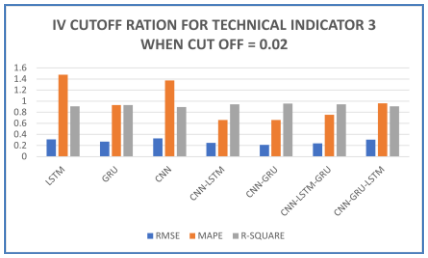
TABLE III. NORMALIZED VALUES TECHNICAL INDICATOR 3

		EXISTING MODELS			*PROPOSED ENSEMBLED MODELS*			
When IV-Cutoff=0.01	**MODELS**	LSTM	GRU	CNN	CNN-LSTM	CNN-GRU	**CNN-LSTM-GRU**	CNN-GRU-LSTM
	RMSE	0.3240	0.4068	0.3066	0.2838	0.2608	**0.2534**	0.2828
	MAPE	1.6371	1.8003	1.3034	0.8630	0.7324	**1.0167**	0.5569
	$\boldsymbol{R^2}$	0.8985	0.8401	0.9091	0.9221	0.9343	**0.9379**	0.9227
		EXISTING MODELS			*PROPOSED ENSEMBLED MODELS*			
When IV-Cutoff=0.02	**MODELS**	LSTM	GRU	CNN	CNN-LSTM	CNN-GRU	CNN-LSTM-GRU	CNN-GRU-LSTM
	RMSE	0.3098	0.2718	0.3295	0.2453	0.2116	0.2394	0.3063
	MAPE	1.4753	0.9284	1.3753	0.6595	0.6606	0.7545	0.9594
	$\boldsymbol{R^2}$	0.9072	0.9286	0.8953	0.9418	0.9567	0.9446	0.9093
		EXISTING MODELS			*PROPOSED ENSEMBLED MODELS*			
	MODELS	LSTM	GRU	CNN	CNN-LSTM	CNN-GRU	CNN-LSTM-GRU	CNN-GRU-LSTM

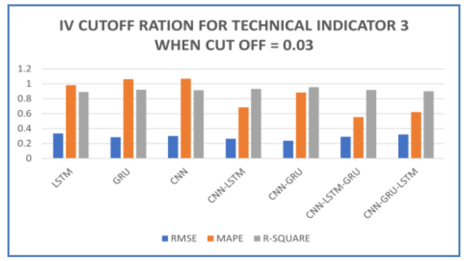
When IV-Cutoff=0.03	**RMSE**	0.3351	0.2837	0.3002	0.2638	0.2359	0.2909	0.3224
	MAPE	0.9801	1.0614	1.0699	0.6866	0.8832	0.5527	0.6227
	R^2	0.8914	0.9222	0.9129	0.9327	0.9562	0.9182	0.8995
	EXISTING MODELS				***PROPOSED ENSEMBLED MODELS***			
When IV-Cutoff=0.04	**MODELS**	LSTM	GRU	CNN	CNN-LSTM	CNN-GRU	CNN-LSTM-GRU	**CNN-GRU-LSTM**
	RMSE	0.2839	0.2901	0.3532	0.2370	0.2888	0.2889	**0.2185**
	MAPE	1.4274	1.0099	1.2319	0.8026	1.0228	0.6041	**0.6074**
	R^2	0.9221	0.9187	0.8794	0.9457	0.9194	0.9193	**0.9583**
	EXISTING MODELS				***PROPOSED ENSEMBLED MODELS***			
When IV-Cutoff=0.05	**MODELS**	LSTM	GRU	CNN	CNN-LSTM	CNN-GRU	CNN-LSTM-GRU	CNN-GRU-LSTM
	RMSE	0.3195	0.3427	0.2858	0.2722	0.2088	0.2612	0.3101
	MAPE	1.6789	1.1028	1.0314	0.7243	0.5320	0.4716	0.6957
	R^2	0.9013	0.8864	0.9211	0.9284	0.9578	0.9340	0.9070



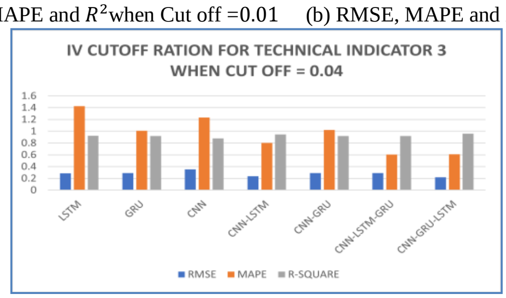
(a) RMSE, MAPE and $R^2$when Cut off =0.01



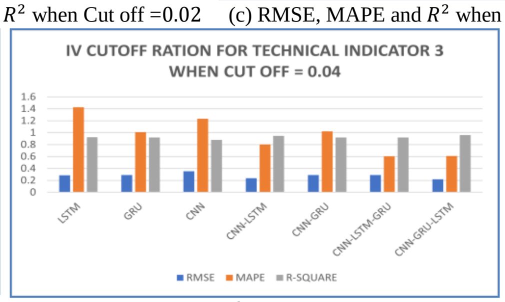
(b) RMSE, MAPE and R^2 when Cut off =0.02



(c) RMSE, MAPE and R^2 when Cut off =0.03



(d) RMSE, MAPE and R^2 when Cut off =0.04



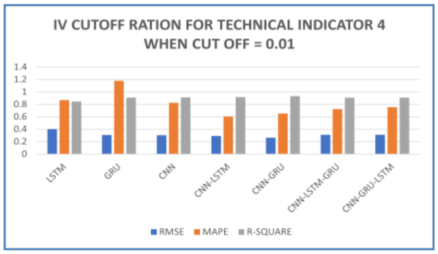
(e) RMSE, MAPE and R^2 when Cut off =0.05

Fig. 4. Comparison of RMSE, MAPE and R^2 of existing and proposed Models for Technical Indicator 3.

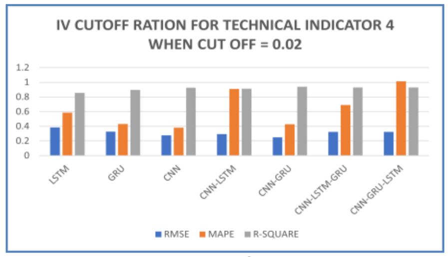
TABLE IV. NORMALIZED VALUES TECHNICAL INDICATOR 4

	EXISTING MODELS				***PROPOSED ENSEMBLED MODELS***			
When IV-Cutoff=0.01	**MODELS**	LSTM	GRU	CNN	CNN-LSTM	CNN-GRU	CNN-LSTM-GRU	CNN-GRU-LSTM
	RMSE	0.4025	0.3057	0.3028	0.2924	0.2630	0.3107	0.3096
	MAPE	0.8684	1.1769	0.8240	0.6068	0.6541	0.7239	0.7545
	R^2	0.8433	0.9097	0.9114	0.9174	0.9331	0.9067	0.9073
	EXISTING MODELS				***PROPOSED ENSEMBLED MODELS***			
When IV-Cutoff=0.02	**MODELS**	LSTM	GRU	CNN	CNN-LSTM	CNN-GRU	CNN-LSTM-GRU	CNN-GRU-LSTM
	RMSE	0.3846	0.3269	0.2747	0.2921	0.2489	0.3231	0.3233
	MAPE	0.5857	0.4298	0.3820	0.9106	0.4295	0.6897	1.0152
	R^2	0.8570	0.8967	0.9270	0.9134	0.9401	0.9291	0.9290
	EXISTING MODELS				***PROPOSED ENSEMBLED MODELS***			
When IV-Cutoff=0.03	**MODELS**	LSTM	GRU	CNN	CNN-LSTM	CNN-GRU	CNN-LSTM-GRU	CNN-GRU-LSTM
	RMSE	0.3958	0.3189	0.2924	0.3335	0.2427	0.3408	0.3480
	MAPE	0.8768	0.6223	0.8152	0.6749	0.5132	0.8490	1.1701
	R^2	0.8486	0.9017	0.9174	0.8925	0.9540	0.8877	0.8829
	EXISTING MODELS				***PROPOSED ENSEMBLED MODELS***			
When IV-Cutoff=0.04	**MODELS**	LSTM	GRU	CNN	CNN-LSTM	CNN-GRU	CNN-LSTM-GRU	**CNN-GRU-LSTM**
	RMSE	0.4068	0.3088	0.2831	0.2783	0.2517	0.3793	0.3543
	MAPE	0.8161	0.8242	0.7760	0.5137	0.4152	0.5721	0.6925
	R^2	0.8399	0.9078	0.9225	0.9251	0.9388	0.8609	0.8787

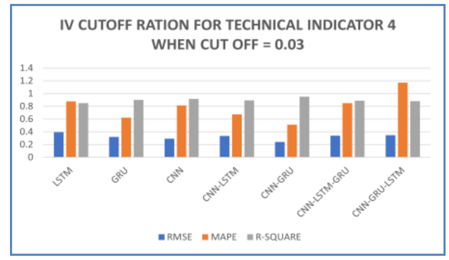
		EXISTING MODELS			***PROPOSED ENSEMBLED MODELS***			
When IV-Cutoff=0.05	**MODELS**	LSTM	GRU	CNN	CNN-LSTM	CNN-GRU	CNN-LSTM-GRU	CNN-GRU-LSTM
	RMSE	0.3690	0.3263	0.2718	0.3133	0.2523	0.3380	0.3359
	MAPE	0.7085	0.5782	0.4247	0.6295	0.5272	0.8943	0.6564
	$\boldsymbol{R^2}$	0.8684	0.8971	0.9286	0.9051	0.9485	0.8996	0.9009



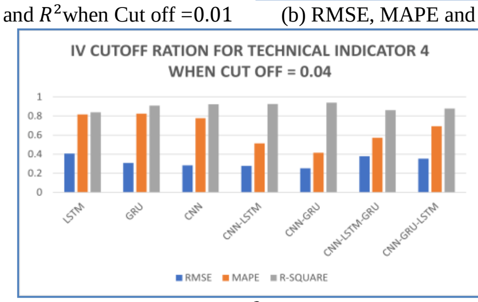
(a) RMSE, MAPE and $R^2$when Cut off =0.01



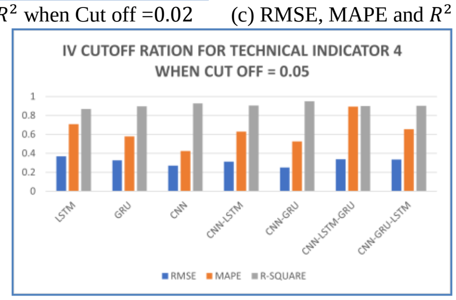
(b) RMSE, MAPE and R^2 when Cut off =0.02



(c) RMSE, MAPE and R^2 when Cut off =0.03



(d) RMSE, MAPE and R^2 when Cut off =0.04



(e) RMSE, MAPE and R^2 when Cut off =0.05

Fig. 5. Comparison of RMSE, MAPE and R^2 of Existing and Proposed Models for Technical Indicator 3.

X. Conclusion and Future Work

In conclusion, this research successfully employed advanced deep learning techniques and key technical indicators to decode the unpredictable price fluctuations of Ripple (XRP). The study achieved exceptional forecasting accuracy through thorough data preprocessing, feature engineering, and the application of sophisticated neural network architectures like the CNN-GRU hybrid. The models improved prediction accuracy and better-understood market trends by using technical indicators like RSI, MACD, and Stochastic Oscillators in deep learning. This shows that combining technical analysis with machine learning can create more accurate prediction models, marking a new step in financial forecasting.

Future research can build on this by including macroeconomic indicators, analyzing sentiment from social media and news, and studying how regulatory changes affect cryptocurrency prices. Expanding the dataset to cover more cryptocurrencies and longer time periods could provide deeper insights into market behavior. These efforts will help understand Ripple's pricing better and support further studies in predicting cryptocurrency trends. We hope and trust as digital assets grow, methods and models will keep evolving to understand their complexities better.

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