Comparative Analysis of Cryptocurrency Price Prediction using Deep Learning

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doi: https://doi.org/10.21467/proceedings.141.10

ABSTRACT

Cryptocurrency is branded as a digital currency, an alternative exchange currency system with significant ramifications for the economies of rising nations and the global economy. In recent years, cryptocurrency has infiltrated almost all financial operations; hence, cryptocurrency trading is frequently recognised as one of the most popular and promising means of profitable investment. Lately, with the exponential growth of cryptocurrency in-vestments, many Alternative Coins (Altcoins) resurfaced as to mimic the fiat currency. Altcoins prediction, as the name suggests the alternative coins from the traditional cryptocurrency which is Bitcoin (BTC). There are several methods to forecast cryptocurrency prices namely Technical Analysis and Fundamental Analysis which has been widely used in forecasting fiat and stock prices. With the emergence of Artificial Intelligence (AI), Machine Learning and Deep Learning algorithms provide a different perspective on how investors can estimate the trend or the movement of prices. In this thesis, as cryptocurrency price are time-dependent, Recurrent Neural Network (RNN) is presented due to RNN's nature that is well suited for Time Series Analysis (TSA). The topology of proposed RNN model consists of 3 stages which are model groundwork, model development and testing and optimisation. The RNN architecture are extended to two different models specifically Long Short-Term Memory (LSTM), Gated Recurrent Unit (GRU). There are 4 hyperparameters that will affect the accuracy of the deep learning model in predicting cryptocurrency price. Hyperparameters tuning set the basis of optimising the model to improve the accuracy of cryptocurrency prediction. Hyperparameters listed in this project are limited to number of epochs, adaptive optimisation algorithm, dropout rate, and batch size. Next, the models are tested with data of different coins listed in the cryptocurrency market with different input features to find out the effect on the accuracy and robustness of the model in predicting the cryptocurrency price. This research demonstrates that GRU has the best accuracy in forecasting the cryptocurrency prices based on the values of Root Mean Square Error (RMSE), Mean Absolute Percentage Error (MAPE) and Executional Time, scoring 2.2201, 0.8076 and 200s using intra-day trading strategy Open, High, Low, Close Price (OHLC) as input features.

Keywords: Cryptocurrency forecasting, deep learning

1 Introduction

Cryptocurrencies have been dubbed a digital currency, an alternative exchange currency system with substantial implications for emerging nations and the global economy [1]. The excitement around cryptocurrency is undeniable, particularly in recent years, as it has permeated virtually all financial activities. As a result, cryptocurrency trading is often regarded as one of the most popular and promising forms of successful investing. Nonetheless, compared to the traditional fiat market, this ever-expanding financial industry is characterized by high volatility and price swings over time. Nowadays, bitcoin forecasting is widely regarded as one of the most challenging time-series prediction issues due to the vast number of

Proceedings DOI: 10.21467/proceedings.141; Series: AIJR Proceedings; ISSN: 2582-3922; ISBN: 978-81-957605-4-1

unknown variables and the extreme volatility of cryptocurrency values, which results in complex temporal dependencies [2].

Predicting market price changes on a constant basis is challenging, however not impossible. According to studies published, market price fluctuations are not random, but instead exhibit a highly nonlinear and dynamic behaviour. Previous research has also demonstrated that it is not required to accurately estimate the future price to profit from financial forecasting. Forecasting the direction of the market relative to its value can result in greater gains [3].

Forecasting with a visualised technical analysis in a graphical pattern or table, it could describe the probabilities of potential crypto market patterns. The main branch of forecasting techniques is time series analysis. Time series is a trend chart of historical data that visualize the trend in series of time. There is a huge variety of ways in forecasting economy indices like stock prices, most of which are time series analysis methods based on structured data.

The basic approach to forecasting cryptocurrency prices is to look for patterns, or what one can refer to as price fluctuations, in the market. Cryptocurrency analysis is extrapolating previous data to forecast future cryptocurrency prices. With the fast advancement of technology, particularly in Artificial Intelligence, experts' educated estimates are made by machines. Many firms implement machine learning and deep learning methods to analyze and forecast data. Nowadays, all financial analysts, crypto market analysts, and scientist are eager to find the most accurate ways to forecast cryptocurrency price movement. Due to its peculiarities and volatile nature, bitcoin price data is more difficult to anticipate than financial time series data. Support Vector Machines (SVM), Artificial Neural Networks (ANN) and Recurrent Neural Network for example, are commonly employed, which is evident in [4], to forecast crypto prices and movements. Every algorithm has a different method for learning patterns and then predicting them [5].

In conventional neural systems, every one of the data sources and yields are autonomous of one another, yet in cases like when it is required to foresee the following expression of a sentence, the past words are required and consequently, there is a need to recollect the past words. Along these lines, RNN appeared, which settled this issue with the assistance of a hidden layer [6]. In this work, we will mainly focus on RNN and the former extensions namely, Gated Recurrent Unit and Long Short-Term Memory

[7] proposed to predict cryptocurrency price by using more a wider dataset, which includes not only prices, but also market cap, volume, circulating and maximum supply. Based on their results obtained on deep learning techniques (RNN and LSTM) the prediction accuracy was within 59% (when using only prices) and up to 75% (on an extended dataset).

[8] conducted prediction on Bitcoin Price, focusing on 3 input variables, Close Price, Gold Price, and Tweets (sentiment). The latter found that GRU outperformed CNN with an RMSE of 179.23, however LSTM was the best model with 151.67. [9] studied the precision with which the direction of the Bitcoin price in United States Dollar (USD) can be predicted. Besides feature selection, they also used Bayesian optimization to select LSTM parameters. The Bitcoin dataset ranged from the 19th of August 2013 to 19th of July 2016. The latter used multiple optimization methods to improve the performance of deep learning methods. The primary problem of their work is overfitting.

Gated Recurrent Unit is another variation of the RNN, which is introduced in 2014. Like LSTM, the GRU is proposed to solve the RNN's shrinking gradient issue, and includes the sigmoid layer, the tanh layer, and the hidden state. However, GRU does not depend on the cell to store memory [10]. Elsewhere GRUs offer

Proceedings DOI: 10.21467/proceedings.141
ISBN: 978-81-957605-4-1

Series: AIJR Proceedings
ISSN: 2582-3922

additional benefits due to having a more straightforward structure [11], predicting the future price using Open, High, Low, Close and Volume Price of historical data which results in GRU having a quite low RMSE at 0.2113. These summary of the different RNN architectures used

To evaluate the possibility of outperforming the market, this paper pays particular attention to deep learning topics for cryptocurrency price predictions. So, the main objective of this paper is to examine cryptocurrency prediction algorithms using artificial intelligence and propose a suitable model for prediction, acquire relevant input features affecting cryptocurrency prices to achieve an accurate result when predicting, develop and optimise the deep learning-based algorithm for cryptocurrency close price prediction, analyse the effect of different trading days and various input features combination on deep learning models prediction and evaluate the performance of the proposed cryptocurrency prediction model.

2 Methodology

In this work, the techniques and methods used in identifying specific parameters or processes is described. Proper selection of certain parameters and specific processes is essential in any research project because every chosen method used for the project must have a valid justification and referencing. So, typically, developing a neural network model for solar forecasting involves many processes and methods, this can be seen in the flow shown in Figure 1 below. This research project requires many steps, activities, and processes before delivering the result. Figure1 shows the phases involved and deliverables.

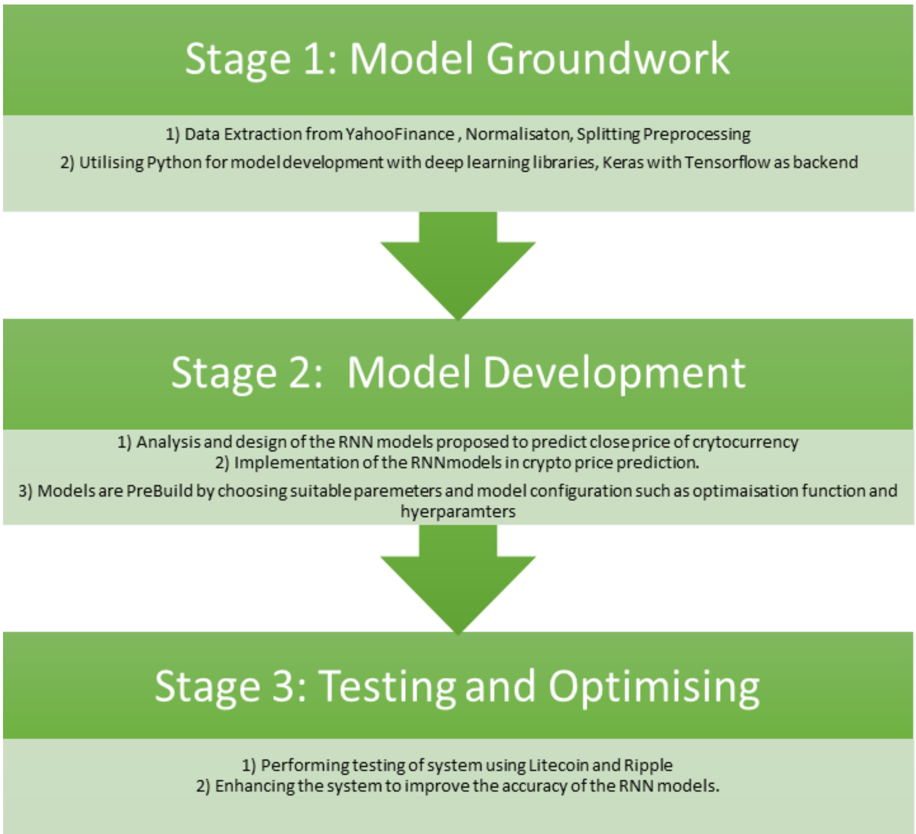
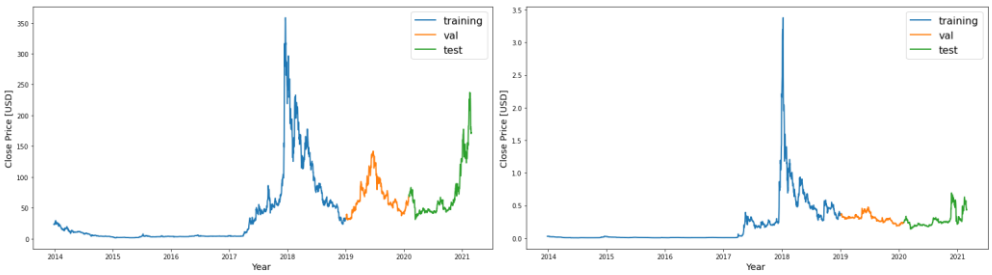


Figure 1: *Research methodology flowchart*

2.1 Model Groundwork

There are a lot of steps taken during Stage 1. Firstly, data is extracted from YahooFinance. The data extracted from YahooFinance is required to be sorted and normalised so that it could be fitted to the RNN model that is used as well providing valid output result for Litecoin (LTC) and Ripple (XRP). The dataset was downloaded with .csv format which have some features like Date Open, High, Low, Close, Volume and Marketcap. The Dataset of 2862 rows of which the row is based on the number of days, totaling up to 16,902 data points to be trained. Input features for the model set up is Close Price as the targeted predicted output is Close Price. The process for deploying the RNN model in predicting cryptocurrency price involves 3 stages. In Stage 1, to train the model, dataset was collected from YahooFinance containing historical price information from a rank 10 cryptocurrency: LTC and XRP. Dataset is gathered based on daily prices starting from 29th April 2013 – 27th February 2021. Data normalization is performed to increase the model's efficiency and accuracy.

In Stage 2, RNN-LSTM will be deployed as the predictive model. The model will be split into 3 parts which are training, validating, and testing. According to [12], data splitting is divided into train 70%, remaining 30% for both validation and test. Dataset is divided into a training set: observations between 29 April 2013-21 October 2018, which is 1988 trading days, a validation from 22 October 2018- 23 December 2019 having 415 days and testing from 24 December 2019- 27 February 2021 also consist of 415 trading days. Similar data splitting is done for different altcoin, which is Ripple (XRP), whereby, Dataset is divided into a training set: observations between 5 August 2013 – 20 November 2018 which is 1934 trading days, a validation from 7 November 2018 - 9 January 2020 (400 trading days) testing from 10 January 2020-27 February 2021 having 400 trading days. Models are then tuned to achieve optimum prediction by tuning the hyperparameters. In Stage 3, models are then tested, comparing the actual and predicted price. Enhancing is done by feeding different input features combination to the proposed models.



(a) LTC Dataset (b) XRP Dataset

Figure 2: *Training, Validation and Testing splitting of LTC and XRP close price history*

The Correlation Analysis is a method of analyzing the linear relationship between two variables. The two variables can be independent or correlated, and the strength of the relationship between two variables is called correlation. The correlation analysis uses the Pearson correlation coefficient. The Pearson correlation coefficient is a measure of the linear correlation between two variables. The correlation of Open, High, Low, Close, Volume (OHLCV) and MarketCap can be seen as below,

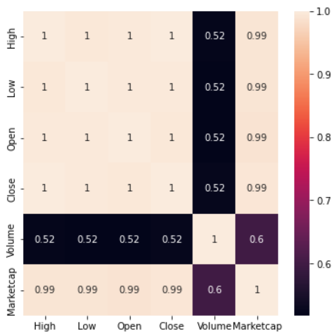


Figure 3: *Heatmap of features correlation*

Table 1: *Features selected based on intraday trading strategy*

Features	Description
Date	Date of observation.
Open	Opening price on the given day.
High	Highest price on the given day.
Low	Lowest price on the given day.
Close	Closing price on the given day.
Volume	Volume of transactions on the given day.

2.2 Model Development

As the RNN model is developed and modified, the most important function in the RNN is as below: the best combination of parameters. Hyperparameters are tuned to achieve the optimum predictive model.

A comparative analysis of RNN models is examined. There are 4 hyperparameters to be manipulated in the LSTM and GRU. The first parameter is number of epochs, followed by Adaptive Optimisation Algorithm, Batch Size and Dropout Rate. This is so that we can yield the best outcome from each classifier before finally choosing the best one. The following section discusses the parameters that can be optimized, and the best parameters are summarized in Table 3, together with the metric used to measure their performance.

2.2.1 Determine Optimum No. of Epoch

In terms of artificial neural networks, an epoch refers to one cycle through the full training dataset. Usually, training a neural network takes more than a few epochs. In other words, if a neural network is fed with the training data for more than one epoch in different patterns, a better generalization is hoped when given a new "unseen" input (test data). In this experiment, the parameter of the model whereby the number of epochs is analyzed. The hyperparameter is tested to the training set of LTC data. The number of epochs used are 20,40,60,80, 100.

Table 2: *Effect of epoch number on LSTM and GRU*

Models	Number of Epoch	RMSE
LSTM	20	5.1693
	40	3.226
	60	0.1993
	80	**0.00736**
	100	0.6743
GRU	20	5.7259
	40	3.7321
	60	2.0293
	80	0.9216
	100	**0.0693**

2.2.2 Determine Optimum Optimisation Algorithm

Optimization algorithms are used to update weights and biases of a model to reduce error. Optimization algorithms can be divided into two main categories, which are constant learning rate algorithm and adaptive learning algorithm. The common first order optimization functions are Stochastic Gradient Descent (SGD), RMSProp and Adam. In this experiment, the parameter of the model whereby the adaptive optimizer is analyzed. The hyperparameter is tested to the training set of LTC data. The optimizer used are Adam and RMSprop. For example, the gradient can get stuck in local minima or flat regions RMSProp algorithm is a modified version of AdaGrad algorithm which goals is to perform better with non-convex function [13]. Adam developed by [14] is another adaptive algorithm and is nowadays one of the most used optimization algorithms.

Table 3: *Effect of Optimisation algorithm on LSTM and GRU*

Models	**Optimiser**	**RMSE**
LSTM	**Adam**	**2.0982**
	RMSProp	2.6613
GRU	**Adam**	**1.6474**
	RMSProp	3.3573

2.2.3 Determine Optimum Batch Size

The batch size limits the number of samples to be shown to the network before a weight update can be performed. This same limitation is then imposed when making predictions with the fit model. Specifically, the batch size used when fitting. the model which controls how many predictions that must be made at a time. This does become a problem making fewer predictions than the batch size. For example, you may get the best results with a large batch size but are required to make predictions for one observation at a time on something like a time series or sequence problem. [15] uses 32 batch size while [16] uses 128 as batch size. In this experiment, the parameter of the model whereby the batch size is analysed. The hyperparameter is tested to the training set of LTC data. The batch size used are 32,64 and 128**.**

Table 4: *Effect of Batch Size on LSTM and GRU*

Models	**Batch Size**	**RMSE**
LSTM	32	2.3060
	64	2.9178
	128	**0.1993**
GRU	**32**	**0.9216**
	64	1.8813
	128	2.6249

2.2.4 Determine Optimum Dropout Rate

Dropout is a strategy that is designed to handle 2 major concerns overfitting, and bigger number of neurons. It prevents overfitting and enables the efficient combination of an exponentially large number of distinct neural network topologies [11]. The word "dropout" refers to units in a neural network that are no longer active (both hidden and apparent). By dropping a unit from the network, we mean temporarily disconnecting it from all of its incoming and outgoing connections. The units to be dropped are chosen at random. In this experiment, the parameter of the model whereby the batch size is analysed. The hyperparameter is tested to the training set of LTC data. The dropout rate used are 0.1, 0.2, 0.4, 0.5 and 0.7.

Table 5: *Effect of Dropout Rate on LSTM and GRU*

Models	Dropout Rate	RMSE
LSTM	**0.1**	**1.8503**
	0.2	1.8666
	0.4	2.9457
	0.5	2.9968
	0.7	1.9969
GRU	**0.1**	**1.6014**
	0.2	1.9527
	0.4	3.3642
	0.5	3.0203
	0.7	1.6015

Table 6: *Summary of Optimum Hyperparameter of Each Models*

Model	Epoch No	Dropout Rate	Optimiser	Batch Size
LSTM	80	0.1	Adam	128
GRU	100	0.1	Adam	32

2.3 Model Enhancement and Evaluation

The combinations are selected based on the correlation weight of features towards the predicted output. Open Price, High Price, Low Price, Close Price are selected as a prediction benchmark which is similarly used by [17] which the latter used similar models to analyse their performances when predicting the close price of cryptocurrency.

In this experiment, the models are tested with different combination input features using the LTC and XRP dataset. The experiment will be carried out with four different input features combinations according to the cases namely, Close Price for a univariate model, Open Price, High Price, Low Price, Close Price (OHLC), Open Price, High Price, Low Price, Close Price and Market Cap (OHLCM) and Open Price, High Price, Low Price, Close Price, Volume and Market Cap (OHLCVM). For novelty purposes, only simulations of testing data on predicting close price of LTC and XRP with OHLCM and OHLCVM input features are shown below,

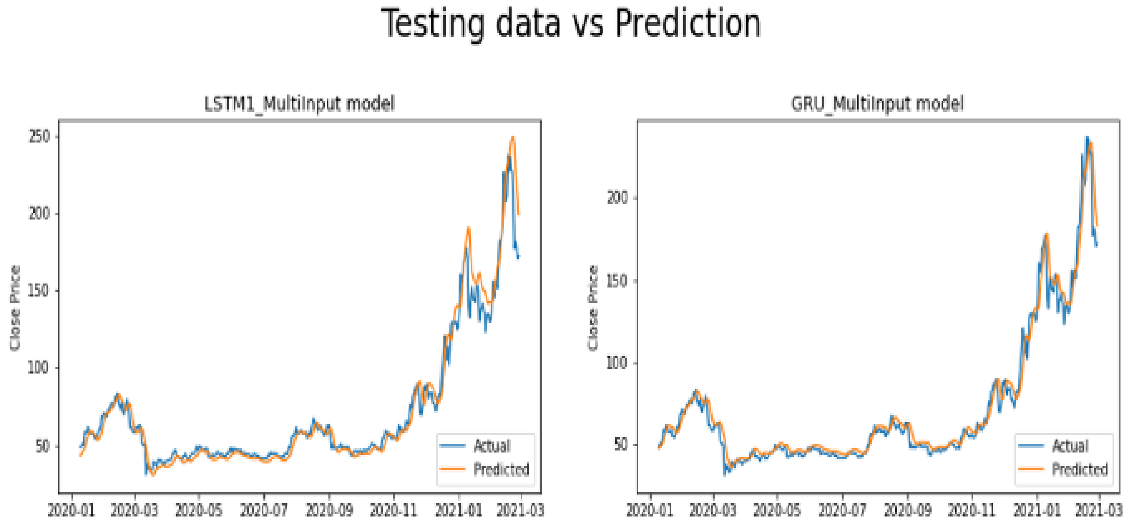


Figure 4: *Testing against prediction plot using LSTM and GRU with OHLCM as input features (LTC dataset)*

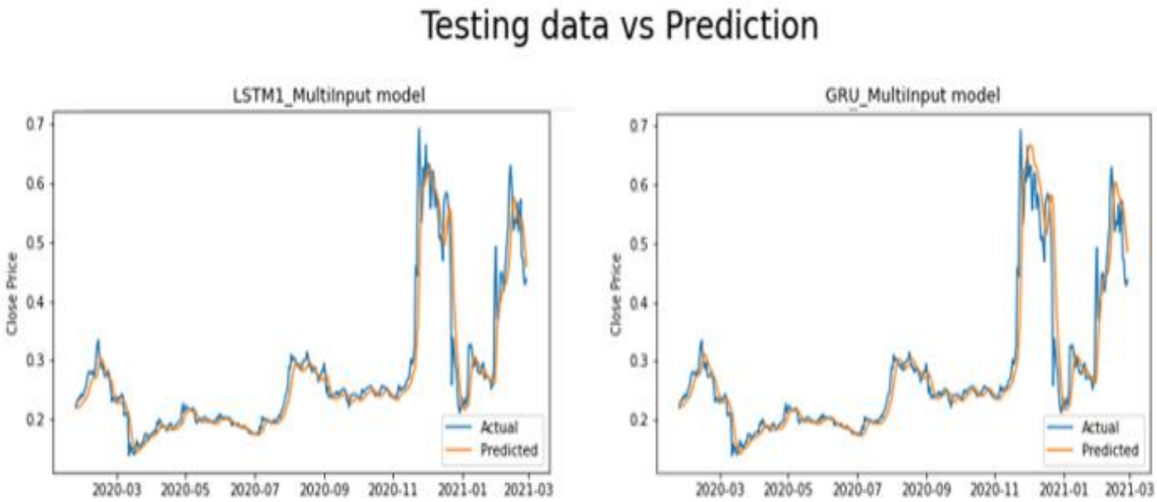


Figure 5: *Testing against prediction plot using LSTM and GRU with OHLCM as input features (XRP dataset)*

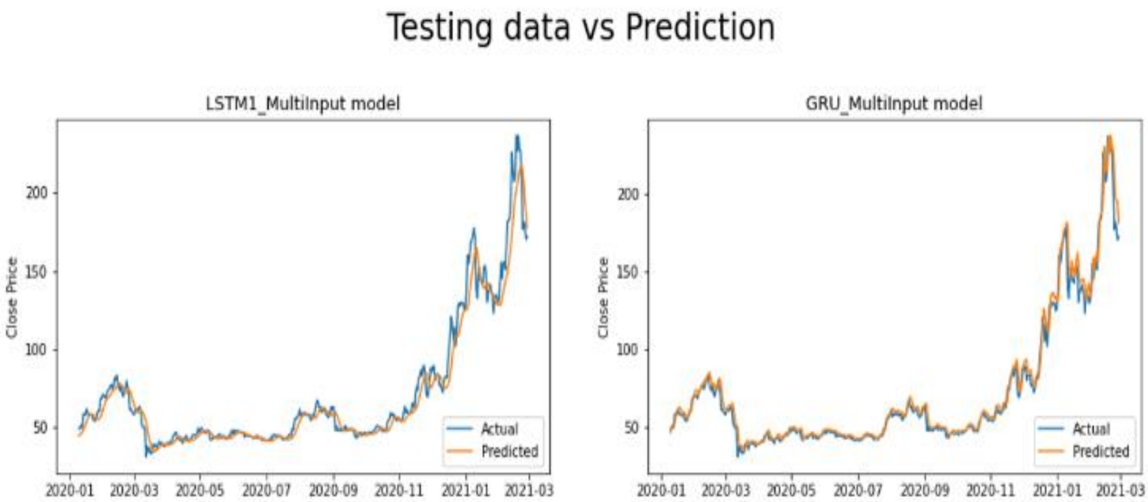


Figure 6: *Testing against prediction plot using LSTM and GRU with OHLCVM as input features (LTC dataset)*

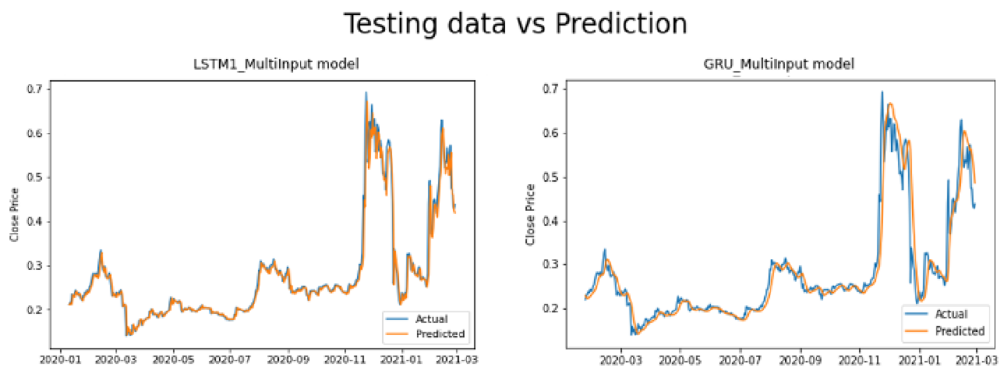


Figure 7: *Testing against prediction plot using LSTM and GRU with OHLCVM as input features (XRP dataset)*

Table 8: *Comparison of current results with existing work*

t	Input Features	Model	Result					
			RMSE		MAPE (%)		Time (s)	
			LTC	XRP	LTC	XRP	LTC	XRP
[17]	OHLC Price	LSTM	3.0690	NA	0.8474	NA	NA	NA
		GRU	**0.8250**	NA	0.2116	NA	NA	NA
[18]	OHLCV Price	LSTM	NA	**0.0979**	NA	6.33	NA	NA
		GRU	NA	0.1042	NA	7.21	NA	NA
This paper	Close Price	LSTM	2.5642	0.1260	0.8893	0.8893	480	480
		GRU	**2.4960**	**0.0237**	0.4888	0.4888	200	200
This paper	OHLC Price	LSTM	3.8869	0.0390	1.3596	1.5791	640	640
		GRU	**2.2201**	**0.0089**	0.8076	0.6620	200	200
This paper	OHLC Price and MarketCap	LSTM	3.2258	**0.0125**	0.7282	0.6020	800	800
		GRU	**3.0567**	0.0192	0.6357	1.4997	600	600
This paper	OHLC Price Volume and MarketCap	LSTM	2.2237	**0.0073**	0.7782	3.4628	800	800
		GRU	**0.9589**	0.0338	0.6659	1.3054	600	600

From Table 8, GRU outperforms LSTM when predicting the price of LTC. Based on previous work done by [17] also found that GRU outperforms LSTM, with 2.201 RMSE value in this paper when OHLC price is treated as input features, which justifies the development and optimization of this model when comparing with [17] findings. The RMSE value obtained from this paper deviates by 1.671 in RMSE and the latter also obtained a RMSE value of 3.069 for LSTM (deviation of 16.44% from this paper). Overall, the MAPE score for all experiments are relatively low <10%, which indicates that the model is accurate in predicting. The MAPE scored by [17] and this paper is not far off; LSTM of 0.8474 and 1.3596 (this paper), GRU of 0.2116 and 0.8076 (this paper). The table above also shows that when the input features increase, GRU has an inconsistent result as the RMSE value fluctuates but still managed to outperform both LSTM when all 6 features are fed. On the other hand, LSTM shows a positive impact when the features increase. Although, the RMSE value spiked when OHLC is tested out, LSTM shows gradual reduction in terms of RMSE value when OHLCM and OHLCVM are experimented. This shows that LSTM is more robust and accurate as more input data are being fed to the model.

Table 8 also depicts the RMSE value when XRP are used as dataset which underwent similar experiment from [18] successfully verified that LSTM network is the most effective model when predicting the close price of XRP. The latter however used a different input feature which involves OHLC Price and Volume. LSTM outperforms GRU when all 6 features OHLCVM are treated as input, in contrast to when LTC is utilised. LSTM scored an astonishing 0.0073 in RMSE value scoring better than [18] findings; 0.0979 in RMSE. Again, for single input features GRU performs the best with the lowest RMSE score of 0.0237, which is logical since GRU having a faster computational time and accomplished better result due to having only update and reset gate. As a matter of fact, a simpler model like GRU, caters for a smaller dataset size while high complexity model namely LSTM is far superior when dataset size broadens.

3 Conclusion

This paper discusses on the forecasting cryptocurrency prices using deep learning models as a tool for cryptocurrency investors. The proposed forecasting model has been made based on the studied reviews which is Recurrent Neural Network (RNN). Performance scores – RMSE, MAPE and computational time - were calculated for LTC and XRP to test the accuracy of the proposed models. The hyperparameters that are optimum for LSTM and GRU are dropout rate of 0.1 and optimization algorithm of Adam. Meanwhile for batch size and epochs varied for both models with LSTM works best with epoch number 80 and batch size 128 while GRU works best with epoch number 100 and batch size 32. Based on these outcomes, the GRU model performance when predicting for the targeted cryptocurrencies can be considered efficient and reliable. This model is considered the best model however, LSTM models showed superiority when the number of input features fed increased, indicating the memory capacity of the model's architecture in predicting a time large time series data as evident in XRP. For the extension of this work, sentiment analysis should be considered as a factor on how they influence the cryptocurrency price as well as performing dimensionality reduction technique to further experiment the performance of higher complexity models namely LSTM. Table 9 and 10 depicts the best-case result for LSTM and GRU based on the experiment conducted.

Table 9: *Results summary for the experiment conducted for LSTM and GRU for LTC*

Models	Optimum Hyperparameters	Trading day(s)	Input Features (lowest RMSE)
LSTM	Epoch No : 80 Batch Size :128 Dropout Rate :0.1 Optimiser :Adam	1	-

GRU	Epoch No : 100 Batch Size :32 Dropout Rate :0.1 Optimiser : Adam	1	Close Price = **2.4960** OHLC Price = **2.2201** OHLCM= **3.0567** OHLCVM = **0.9589**

Table 10: *Results summary for the experiment conducted for LSTM and GRU for XRP*

Models	Optimum Hyperparameters	Trading day(s)	Input Features (lowest RMSE)
LSTM	Epoch No : 80 Batch Size :128 Dropout Rate :0.1 Optimiser :Adam	1	OHLCM= **0.0125** OHLCVM = **0.0073**
GRU	Epoch No : 100 Batch Size :32 Dropout Rate :0.1 Optimiser : Adam	1	Close Price = **0.0237** OHLC = **0.0089**

4 Declarations

4.1 Competing Interests

There is no conflict of interest.

4.2 Publisher's Note

AIJR remains neutral with regard to jurisdiction claims in published maps and institutional affiliations.

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Proceedings DOI: 10.21467/proceedings.141
ISBN: 978-81-957605-4-1

Series: AIJR Proceedings
ISSN: 2582-3922