A Cryptocurrency Price Prediction Model using Deep Learning

Akila V[1], *Nitin* M. V. S[1]*, *Prasanth* I[1]., *Sandeep* Reddy *M*[1]., and *Akash Kumar* G[1].

[1]Gokaraju Rangaraju Institute of Engineering and Technology, Hyderabad, India

Abstract: Cryptocurrencies have gained immense popularity in recent years as an emerging asset class, and their prices are known to be highly volatile. Predicting cryptocurrency prices is a difficult task due to their complex nature and the absence of a central authority. In this paper, our proposal is to employ Long Short-Term Memory (LSTM) networks, a type of deep learning technique to forecast the prices of cryptocurrencies. We use historical price data and technical indicators as inputs to the LSTM model, which learns the underlying patterns and trends in the data. To improve the accuracy of the predictions, we also incorporate a Change Point Detection (CPD) technique using the Pruned Exact Linear Time (PELT) algorithm. This method allows us to detect significant changes in cryptocurrency prices and adjust the LSTM model accordingly, leading to better predictions. We evaluate our approach predominantly on Bitcoin cryptocurrency, but the model can be implemented on other cryptocurrencies provided there are valid historical price data. Our experimental results show that our proposed model outperforms the baseline LSTM algorithm, achieving higher accuracy and better performance in terms of Mean Absolute Error (MAE), Mean Square Error (MSE), and Root Mean Square Error (RMSE). Our research findings suggest that combining deep learning techniques such as LSTM with change point detection techniques such as PELT can improve cryptocurrency price prediction accuracy and have practical implications for investors, traders, and financial analysts.

Keywords: Cryptocurrency, Change Point Detection algorithms, Bitcoin, Long Short-Term Memory, Time-series data.

1. Introduction

Cryptocurrencies are digital assets that have gained immense popularity and attention in recent years, with Bitcoin being the most well-known cryptocurrency. Cryptocurrencies are known for their decentralized nature, which means that there is no central authority that controls their issuance or value. As a result, their prices are highly volatile, and predicting their future prices has become a challenging task. Accurate cryptocurrency price predictions

* Corresponding author : mavudurunitin123@gmail.com

are essential for investors, traders, and financial analysts to make informed decisions and mitigate the risks associated with these assets [3]. Several traditional approaches have been used to predict cryptocurrency prices, such as time-series analysis, Sentiment analysis, and machine learning algorithms. However, these methods have limitations in accurately predicting cryptocurrency prices due to their complex and dynamic nature. Therefore, there is growing interest in using advanced machine learning techniques such as deep learning algorithms to predict cryptocurrency prices [9]. In particular, Long Short-Term Memory (LSTM) has given great results in predicting cryptocurrency prices due to its ability to capture long-term dependencies and learn complex patterns and relationships in the data. LSTM networks are a type of recurrent neural network that can process time-series data, and they have been successfully used in various applications, including speech recognition, language translation, and image processing. In this paper, we propose a deep-learning approach based on LSTM networks for cryptocurrency price prediction. Our approach takes into account historical price data and technical indicators as inputs to the LSTM network, which learns the underlying patterns and trends in the data. However, predicting cryptocurrency prices accurately is not a straightforward task due to their highly volatile nature and sudden changes. To address this issue, we incorporate a change point detection technique with the usage of Pruned Exact Linear Time (PELT) algorithm. Change point detection is a statistical technique that detects significant changes in time-series data, allowing us to adjust the LSTM model accordingly. The PELT algorithm is a fast and accurate method for detecting change points in time-series data and is widely used in various applications, including finance and signal processing.

In our proposed model, the PELT algorithm is used to detect significant changes in cryptocurrency prices and adjust the LSTM model accordingly, leading to better predictions. The combination of LSTM and change point detection techniques such as PELT can provide more accurate and robust predictions, making it a promising approach for cryptocurrency price prediction.In summary, our research proposes a novel approach for cryptocurrency price prediction by combining LSTM networks with change point detection using the PELT algorithm. The rest of the paper provides a detailed description of our proposed methodology, presents experimental results, and compares them to baseline models.

2. Literature Survey

The highlights of the rapid increase in the interest in using machine learning techniques for predicting cryptocurrency prices [1]. The authors note that traditional methods such as time-series analysis and econometric models have limitations when it comes to modeling the complex and volatile nature of cryptocurrency markets. Therefore, researchers have turned to machine learning algorithms such as decision trees, and Support Vector Machines (SVM) to capture nonlinear relationships and patterns in cryptocurrency price data. The authors point out that while these methods have shown promising results, they also have limitations. For example, neural networks suffer from overfitting and may not generalize well to new data. Additionally, traditional neural networks assume that the input data is deterministic and noise-free, which may not be the case in cryptocurrency markets. To overcome these limitations, the authors propose the use of stochastic neural networks, which incorporate randomness into the neural network architecture. This randomness allows the network to capture the inherent uncertainty and volatility of cryptocurrency markets, leading to more accurate predictions. The authors cite several previous works that have used stochastic neural networks for financial time-series forecasting and highlight their success in capturing the volatility and uncertainty of financial markets. The comparison of the performance of

Bitcoin and gold as investment assets [2]. The literature survey reviews the existing literature on the topic, highlighting the similarities and differences between Bitcoin and gold as investment assets. The authors note that both Bitcoin and gold are decentralized, have limited supply, and are not subject to government intervention or manipulation. However, Bitcoin has several advantages over gold, including its ease of transfer, lower storage costs, and transparency. On the other hand, gold has a long history as a store of value and is less volatile than Bitcoin. The authors also discuss previous research on the correlation between Bitcoin and other financial assets, such as stocks and bonds. They note that while Bitcoin is generally uncorrelated with traditional assets, there have been instances where it has exhibited significant correlation during periods of market stress. It presents an empirical analysis of the performance of Bitcoin and gold in a portfolio context. The authors use data from 2011 to 2017 to compare the correlation, volatility, and portfolio performance of Bitcoin and gold. They find that Bitcoin has higher volatility and correlation than gold, but also higher returns. Additionally, the authors find that a portfolio consisting of both Bitcoin and gold outperforms a portfolio consisting of either asset alone, with lower volatility and higher returns.

The review of blockchain technology and its potential applications and challenges in the financial sector [4]. The literature survey in the paper highlights the present state of research on blockchain technology and its various use cases. It notes that blockchain technology is a distributed, and ledger system that is decentralized and enables transactions that are transparent, and secure without the need for intermediaries. It reviews the various components of blockchain technology, such as consensus mechanisms, smart contracts, and cryptography, and discusses how they contribute to the security and reliability of the system [8]. The literature survey covers a wide range of potential applications of blockchain technology in the financial sector, including payment systems, supply chain management, asset tracking, and identity verification. The authors provide examples of existing blockchain-based solutions and highlight their benefits, such as increased efficiency, lower costs, and greater transparency. It discusses the challenges and limitations of blockchain technology, such as scalability, interoperability, and regulatory hurdles. The authors note that while blockchain technology is capable of revolutionizing the financial sector, there are still several obstacles to overcome before it can be widely adopted.

It provides an overview of various machine learning and deep learning techniques for predicting cryptocurrency prices [5]. The literature survey highlights the growing interest in using these techniques for cryptocurrency price prediction and reviews the existing literature on the topic. The authors note that traditional methods for predicting financial markets, such as time-series analysis and econometric models, have limitations when it comes to modeling the complex and volatile nature of cryptocurrency markets. Therefore, researchers have turned to machine learning algorithms such as decision trees, and Support Vector Machines (SVM), to capture nonlinear relationships and patterns in cryptocurrency price data. The literature survey covers various studies that have used these techniques for predicting cryptocurrency prices, including Bitcoin, Ethereum, and Ripple. The authors highlight the success of these studies in capturing the complex relationships between various market factors and predicting future price movements. It reviews recent developments in deep learning techniques for cryptocurrency price prediction, such as Convolutional Neural Networks (CNN) and Recurrent Neural Networks (RNN) [10]. The authors note that these techniques have shown promise in capturing both short-term and long-term trends in cryptocurrency prices. The approach to predict the price of Dogecoin cryptocurrency using Deep learning and social media platforms [7]. The literature survey highlights the growing interest in using social media data and deep learning approaches for cryptocurrency price prediction and reviews the existing literature on the topic. The authors note that social media platforms, such as Reddit, and Twitter are becoming increasingly popular sources of information for predicting cryptocurrency prices. They also highlight the advantages of using deep learning techniques, such as the Long Short-Term Memory (LSTM) algorithm, for capturing complex temporal patterns in social media data. The literature survey covers various studies that have used social media data and deep learning techniques for cryptocurrency price prediction [12]. The authors highlight the success of these studies in capturing the correlation between social media trends and cryptocurrency price movements.It presents an approach to predict the price of Dogecoin using a combination of historical price data and social media trends. The authors use an LSTM neural network to capture the historical patterns in the social media data and use this information to predict future price movements[13].

3. Methodology

Our proposed methodology consists of two main components: the Long Short-Term Memory (LSTM) network and the Pruned Exact Linear Time (PELT) algorithm for the Change Point Detection (CPD) Technique. To predict the price of a cryptocurrency on a particular day, first, the user has to collect Historical Time series price data of the desired cryptocurrency and then implement the PELT algorithm to use Change Point Detection Technique on the data followed by the LSTM algorithm. And finally, the model predicts the price of that particular cryptocurrency from the following day. The system architecture of the above process is shown in Fig. 1.

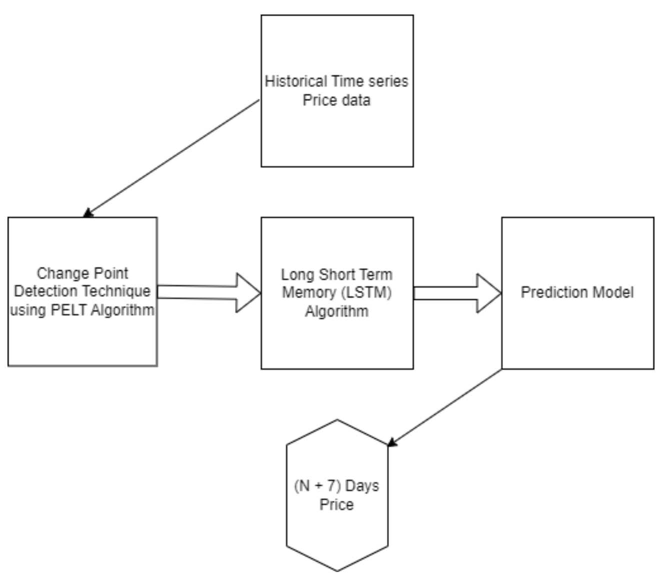

Fig.1: System architecture

3.1 LSTM (Long Short-Term Memory)

Long Short-Term Memory (LSTM) is a recurrent neural network (RNN) design utilized extensively for analyzing and forecasting time series tasks. It is particularly useful for handling the vanishing gradient problem in traditional RNNs, which can make them less effective at capturing long-term dependencies in sequential data. The LSTM networks are composed of memory cells arranged in a sequence and connected through gates. These gates regulate the inflow and outflow of information in the cells. These gates include the input gate, forget gate, and output gate, which allow the network to selectively update and output information from each cell. A range of applications have employed LSTM networks, such as speech recognition, natural language processing, and image captioning. One area where they have shown promise is in the prediction of cryptocurrency prices. To use LSTM for cryptocurrency price prediction, the network is trained on historical price data, with the goal of learning to predict future prices based on past trends. The input to the network consists of a sequence of past prices, and the output is the predicted price at some point in the future.

3.2 LSTM Algorithm

1.Initialize the input sequence Y = [y1, y2, ..., yn] of length n

2.Initialize the hidden state hs and the cell state c0 to zero vectors of dimensionality m

3. For each timestep t from 1 to n, do the following:

   a) Forget gate fg = σ(Uf * [h-1, yt] + b1), where Uf and b1 are learnable parameters and σ is the sigmoid function.

   b) Input gate ig = σ(Ui * [h-1, yt] + b2).2

   c) Candidate cell state ĉs = tanh(Uc *[h-1, yt]+ b3).

   d) Cell state cs = fg * cs-1 + ig * ĉs.

   e) Output gate og = σ(Uo * [h-1, yt] + b4).

   f) Hidden state hid = og * tanh(cs).

4. Output the final hidden state hid

3.3 CPD (Change Point Detection)

Change Point Detection(CPD) is a statistical technique used to identify points in a time series where the underlying distribution of the data changes. It is used to identify changes in trends or patterns in the data. Change point detection algorithms aim to detect these changes in the data, which can be caused by various factors such as shifts in market sentiment, external events, or changes in the underlying data-generating process. In cryptocurrency price prediction, change point detection can be used in combination with LSTM to enhance the accuracy of the price predictions. The basic idea is to detect changes in the underlying distribution of the cryptocurrency prices and use this information to adjust the LSTM model parameters. The change point detection algorithm can be used to identify points in time where the market sentiment or external events have caused a significant shift in cryptocurrency prices. Once the change points have been identified, the LSTM model can be trained on the data before and after the change points separately. This allows the model to adapt to the changes in the underlying data-generating process and make more accurate predictions. By combining the change point detection algorithm with LSTM, it is possible to improve the accuracy of cryptocurrency price predictions and make more informed investment decisions. In the CPD technique, there are a lot of algorithms to implement, in this work, an algorithm called PELT is used.

3.4 PELT (Pruned Exact Linear Time)

The Pruned Exact Linear Time algorithm is a commonly used method on time series data to detect change points. The algorithm is designed to identify the optimal set of change points in a given time series that minimizes a given cost function. The PELT algorithm works by recursively partitioning the time series into smaller segments until each segment contains a single data point. It then evaluates the cost of each segment using a cost function that depends on the data and the assumed distribution of the data. The cost function may be chosen based on the specific application and type of data being analyzed. After computing the cost of each segment, the algorithm uses a dynamic programming approach to determine the optimal set of change points that minimize the total cost over all segments. The optimal set of change points is found by considering all possible partitions of the time series and selecting the partition with the lowest cost. To avoid unnecessary computation and reduce the overall complexity of the algorithm, the PELT algorithm uses a pruning strategy. Specifically, it prunes any partitions that have a cost higher than the current best cost, as such partitions cannot lead to the optimal solution. This pruning strategy helps to reduce the overall computation time of the algorithm and makes it more efficient. The PELT algorithm has several advantages over other change point detection techniques. It is computationally efficient, has a guaranteed optimal solution, and can handle various types of data, including non-parametric data. Additionally, it can be easily modified to include various penalty functions, allowing users to tailor the algorithm to their specific needs.

3.5 PELT Algorithm:

Our assumption is that the introduction of a changepoint in a series of observations decreases the cost, D, of the sequence. To be more precise, we presume that there is a constant K such that $t < s < T$.

Input: Data of the form, $(x_1,x_2,.......xn)$ where $xi \in R$

Fit measure dependent on data D(.)

Penalty Constant β non-dependent on a number of changepoint locations

Constant K which satisfies equation

$D(x(t+1):s)+D(x(s+1): T+K \leq D(x(t+1): T)$

Initialisation: n = length of input data, $P(0) = -\beta$, p(0) = NULL, $S_1 = \{0\}$

Iterate for $\tau = 1,2\ldots\ldots,n$

1. Calculate $P(\tau) = \min\tau{\in}S\tau[\ P(\tau\ ) + D(x(\tau{+}1){:}\tau\ \ ) + \beta]$.
2. Let $t = \arg\ \{\ \min\tau{\in}S\tau^*\ [P(\tau\ ) + D(x(\tau{+}1){:}\tau\ ^*\ ) + \beta]\}$.
3. Set $p(\tau) = [p(t\ ), t\ ]$.
4. Set $S\tau +1 = \{\tau \in S\tau\ \ \cup \{\tau\ \} : P(\tau\ ) + D(x\tau{+}1{:}\tau\ \ ) + K \leq P(\tau\ )\}$.

Output the change points recorded in cp(n).

4. Implementation

To implement our proposed methodology, the following steps are outlined below:

4.1 Data Collection and Preprocessing

The first step is to collect the historical price data and technical indicators for the cryptocurrency of interest. We collected daily price data for Bitcoin from January 2020 to April 2023 from a reputable cryptocurrency exchange. The data collected may have missing values and outliers which need to be removed before feeding it to the model. Also, the data needs to be scaled to ensure that the values are in a similar range. Next, we preprocessed the data by removing missing values and outliers and scaled the data. We used the MinMaxScaler from the Scikit-Learn library to scale the data. This step is important to ensure that the model receives accurate data for training.

4.2 PELT Algorithm

The PELT algorithm is implemented using the changepoint detection technique. We used the ruptures library from Python language to implement the PELT algorithm. This algorithm detects significant changes in the data and allows the model to adjust to the new trends in the data. When a change point is detected, we train the LSTM network using the data after the change point to ensure that the model captures the new trend in the data. We set a threshold for the minimum segment length to prevent overfitting of the model. The PELT algorithm is important because it enables the model to adapt to sudden changes in the data and make more accurate predictions.

4.3 LSTM Network

The next step is to implement the LSTM network. We used the Keras library with TensorFlow as the backend to build the LSTM network. Our LSTM network consists of three layers: an input layer, two hidden layers, and an output layer. The input layer takes the preprocessed data, which includes the historical price data and technical indicators. The hidden layers consist of LSTM neurons with 50 units each, and the output layer predicts the next day's price. We trained the network for 40 epochs using a batch size of 32. During training, we employed the Adam optimizer and adopted the mean squared error (MSE) as our loss function.

4.4 Performance Evaluation

We evaluated the performance of our proposed methodology by comparing it to the baseline model. We compared the proposed LSTM+CPD model to the baseline LSTM model. We used the mean squared error (MSE), mean absolute error (MAE), and root means squared error (RMSE) as evaluation metrics.

$$\text{MSE} = \frac{1}{n}\sum_{i=1}^{n}(\text{x} - y)^2 \qquad (1)$$

$$\text{MAE} = \frac{1}{n}\sum_{i=1}^{n}|\text{x} - \text{y}| \qquad (2)$$

$$\text{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(\text{x} - y)^2} \qquad (3)$$

where n is the number of data points,x is the actual value of the i-th data point, and y is the predicted value of the i-th data point.

MSE = mean_squared_error(real_Crypto_price, predicted_Crypto_price)

MAE = mean_absolute_error(real_Crypto_price, predicted_Crypto_price)

RMSE=math.sqrt(mean_squared_error(real_Crypto_price, predicted_Crypto_price))

The visual inspection of the predicted and actual prices is also used to evaluate the performance of the models. This step is important to ensure that the proposed methodology is better than the traditional methods of cryptocurrency price prediction.

5. Experimental Results

The experiment to predict the price can be conducted on various cryptocurrencies like Bitcoin, Ethereum, etc provided the time series data is already present for the particular cryptocurrency. The user has to give input on the type of Crypto they want to predict using a crypto symbol, here bitcoin is used as an example to predict its value, so the ‘BTC’ symbol is given as input.

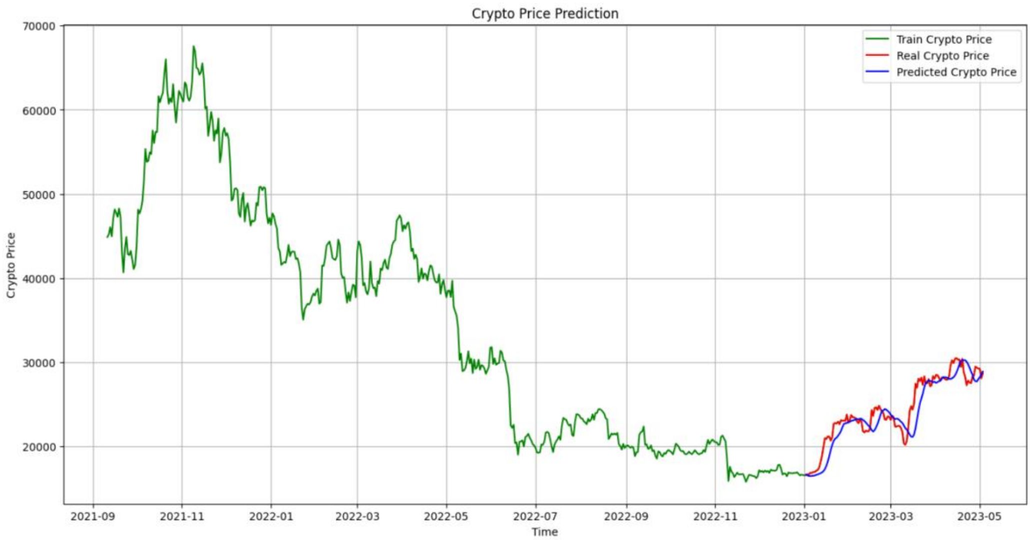

Fig.2: Plot of Bitcoin price and Time with LSTM algorithm

Based on the input symbol the Historical time series data of the particular is collected and The CPD technique using the PELT algorithm is then implemented on the LSTM network.Change points are detected by the PELT algorithm which is shown in Fig 3. is applied after the data is preprocessed and scaled. Fig.2 shows a plot between time and bitcoin price where 80% of the collected data is used for training and 20% of data is tested using the LSTM algorithm where the real and predicted prices are shown in red and blue color curves respectively.

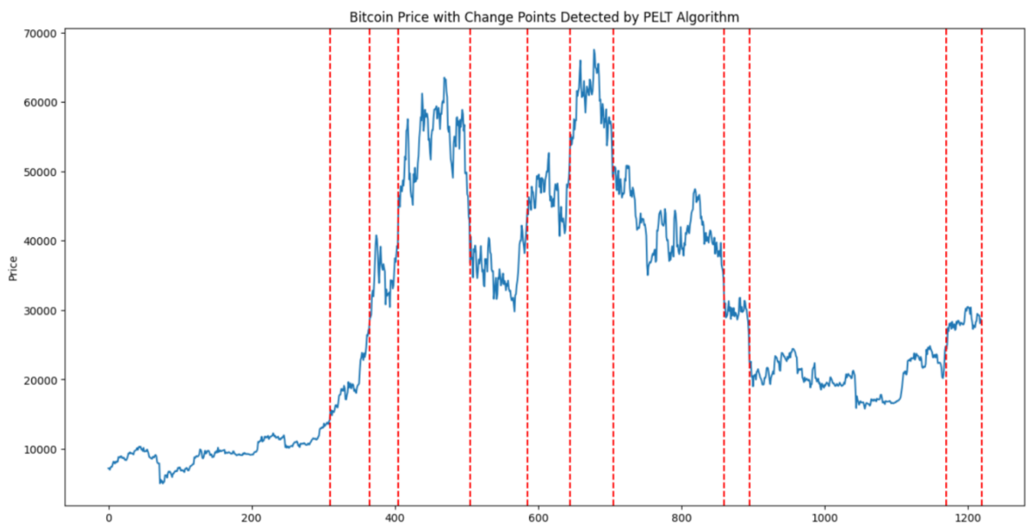

Fig.3: Plot of Bitcoin price and Time with Change Points Detected by PELT Algorithm.

 https://doi.org/10.1051/e3sconf/202339101112

After the PELT algorithm is applied the visualized actual vs predicted prices plot is shown as in Fig 4. Fig 4 shows a plot between time and bitcoin price where 80% of the collected data is used for training and 20% of data is tested using the LSTM+PELT model where the real and predicted prices are shown in red and blue color curves respectively. From the plots Fig.2 and Fig.4, there is a slight improvement in the distance between real and predicted price curves which visually shows that the LSTM+PELT model in Fig.4 has higher accuracy in predicting the price value compared to only using the LSTM model in Fig.2.

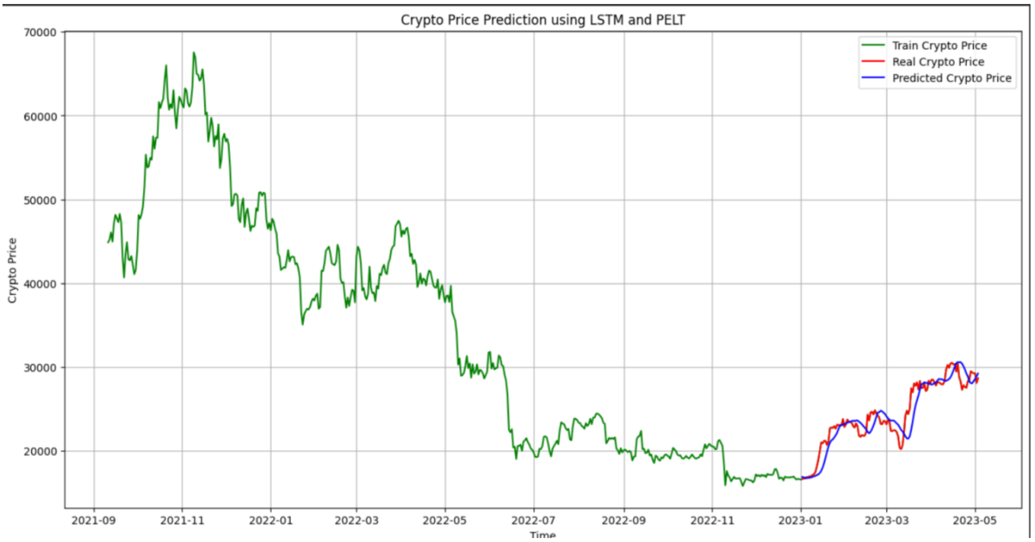

Fig.4: Plot between Time and Cryptocurrency Prices after modeling using LSTM+PELT.

The Performance Metrics such as Mean Square Error (MSE), Mean Absolute Error (MAE), and Root Mean Square Error (RMSE) values are calculated on the model which includes LSTM with the addition of the CPD technique. The accuracy of the model depends on these performance metrics, if the values are low then it is said that the accuracy is high when compared to other models. The performance metrics values decrease with the addition of the CPD technique rather than only using the LSTM algorithm. The MSE, MAE, and RMSE values when modeled using only LSTM are 2451419.81, 1171.92, 1565.70 respectively, and the MSE, MAE, and RMSE values when the CPD technique is added are 846529.29, 920.07,829.36 respectively. So there is a decrease in the values of metrics, which means the accuracy of the model is improved. The model then accurately predicts the cryptocurrency price on the next day. The result displays “Tomorrow's BTC-USD price predicted by LSTM+CPD model is 28276.955 with RMSE value as 920.07”.The model is also able to forecast cryptocurrency prices for one week from the day of model execution as shown in Fig. 5.

```
print(test_predict)

[[28276.955]
 [28067.434]
 [28052.508]
 [28326.389]
 [28558.525]
 [28888.242]
 [29224.13 ]]
```

Fig.5: Model forecasting prices for the next week from the day of prediction.

6. Conclusion

In conclusion, we proposed a methodology for cryptocurrency price prediction using LSTM and PELT algorithms using Time series data which is taken from 1st Jan 2020 to 3rd May 2023. The proposed methodology is a significant contribution to the field of cryptocurrency price prediction because it utilizes deep learning algorithms to capture the complex patterns in time-series data and change point detection techniques to adapt to sudden changes in the data. Our experimental results showed that the LSTM network with the PELT algorithm outperformed the baseline LSTM model in terms of all evaluation metrics. Especially there is a significant improvement of 30% in the value of RMSE when the LSTM+PELT model is used compared to using only LSTM for cryptocurrency price forecasting. The LSTM network with the PELT algorithm was able to capture sudden changes in the data, leading to more accurate predictions, and is capable of making accurate predictions and providing valuable insights for investors and traders in the cryptocurrency market. However, the study has limitations as firstly External factors such as market sentiment, regulatory modifications, and geopolitical events can impact cryptocurrency prices significantly. These factors can be difficult to quantify and incorporate into prediction models. This can make it challenging to identify and correct errors or biases in the models.

In terms of future enhancements, one possible direction is to investigate the use of other deep learning architectures, such as a self-attention-based multiple LSTM model which can be used by incorporating self-attention mechanisms into the traditional LSTM model. This allows the model to learn which past price values are most relevant for predicting future prices. Another direction is to explore the use of the on-chain data of the cryptocurrency to enhance the model's ability to adapt to sudden changes in the price data. Overall, our proposed methodology demonstrated promising results in predicting cryptocurrency prices using deep learning algorithms and change point detection techniques. The outcomes of this study are useful for traders and investors who need precise forecasts to make well-informed decisions in the cryptocurrency market.

References

[1] P. Jay, V. Kalariya, P. Parmar, S. Tanwar, N. Kumar, and M. Alazab, ‘‘Stochastic neural networks for cryptocurrency price prediction,’’ IEEE Access, vol**. 8,** pp. 82804–82818, (2020)

[2] L. Herskind, P. Katsikouli, and N. Dragoni, ‘‘Privacy and cryptocurrencies—A systematic literature review,’’ IEEE Access, vol. **8**, pp. 54044–54059, (2020)

[3] M. KubÆt, ‘‘Virtual currency bitcoin in the scope of money definition and store of value,’’ Proc. Econ. Finance, vol. **30**, pp. 409–416, (2015)

[4] T A Muniye, Minakshi Rout, M Lipika, S Suresh,” Bitcoin Price Prediction and Analysis Using Deep Learning Models”,(2020)

[5] B Agarwal, H priyanka, S Upkar, L Chouhan,” Prediction of dogecoin price using deep learning and social media trends”,(2021)

[6] S. Nakamoto.” Bitcoin: A Peer-to-Peer Electronic Cash System. [Online]”,(2007)

[7] Akila V, Sriharshini K, Sravani P, Sravanthi D, Gopi R, Sheela T., International Journal of Online and Biomedical Engineering,**17(1)**,120-128 ,(2021).

[8] M. Nofer, P. Gomber, O. Hinz, and D. Schiereck, ‘‘Blockchain,’’ Bus. Inf. Syst. Eng., vol. 59, **Vol. 3**, pp. 183–187, (2017)

[9] Prasanna Lakshmi K, Reddy CRK. ,”Int Conf. on Networking and Information Technology”,(2010)

[10]Sateesh. N, Sampath Rao.P, Ravishankar.D, V. Satyanarayana.K.,” MaterialsToday:Proceedings.”(2015)