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CNN and RNN are Predicting a High-Frequency Bit Coin Trend

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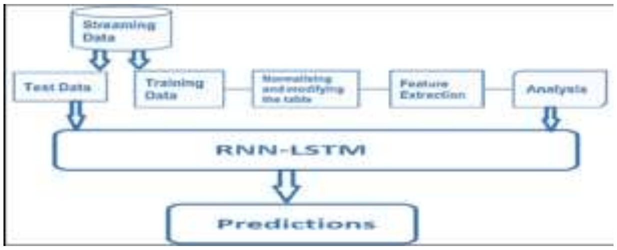
Abstract- Bit coin is a type of digital currency that is used for online transactions. It is a digital currency that does not exist in hard currency form. Our focus is on the distinction between a decentralized currency and a centralized currency, which means that all virtual currency users can acquire services without the aid of a third party. Due to their severe price volatility, the use of these crypto currencies has an impact on international relations and trade. A reliable method for estimating this price is urgently necessary due to the rapid variations in the prices of crypto currencies. The level of one main or central control over them has been significantly affected by price control by a number of organizations, affecting relationships with other businesses and international trade. In addition, the constant oscillations suggest that a more precise method of estimating this price is urgently required. Thus, using deep learning techniques such as the recurrent neural network (RNN) and the long short-term memory (LSTM), gated recurrent unit (GRU), which are effective learning models for training data, we must design a method for the accurate prediction of by considering various factors such as market cap, maximum supply and, volume, circulating supply. Python is used to write the proposed method and it is tested on benchmark datasets. It can be inferred from the results that the proposed method is capable of making reliable predictions. For the past ten years, academics in various fields have used neural networks as one of the intelligent data mining tools. The importance of stock market data cannot be overstated in today's economy. Forecasting methodologies can be divided into two types: linear (AR, MA, ARIMA, ARMA) and nonlinear models (ARCH, GARCH, Neural Network). To anticipate a company's stock price based on past prices, we employed Autoregressive Integrated Moving Average (ARIMA), Recurrent Neural Network, Long Short-Term Memory (LSTM), and Gated Recurrent Unit Deep Learning Architectures (GRU).

Keywords: Bitcoin, Cryptocurrency Price Prediction, Digital Currency, Deep Learning, Recurrent Neural Network (RNN), Long Short-Term Memory (LSTM), Gated Recurrent Unit (GRU), ARIMA, Stock Market Forecasting, Time Series Prediction, Machine Learning, Python, Cryptocurrency Market, Market Capitalization, Financial Forecasting.

I. INTRODUCTION

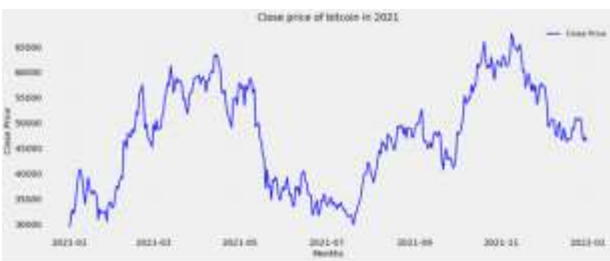
Cryptocurrency is a type of virtual or digital currency in financial systems. The protection of it is provided by encryption, which prevents counterfeiting and double-spending. The difference between it and traditional currencies is that it is not issued by a central authority or central banks, and it is a decentralized virtual currency that can be converted using cryptographic techniques. The other aspect is that it is powered by block chain technology, which is incredibly complicated and aims to store data in such a way that it is difficult or impossible to alter, hack, or cheat the system. Bitcoin's ability to carve out a niche for itself is something that could either lead to widespread acceptance of crypto currencies or spell their doom. It is not clear if crypto currencies will be widely used in global markets or not, as they are still in the experimental phase. Bitcoin, the most popular crypto currency, was established in 2009 and was the only Block chain-based crypto currency for over two years.

Apple's Siri and Google's voice search both employ recurrent neural networks (RNNs) as the state-of-the-art approach for sequential data. This algorithm is designed to use its internal memory to recall input, making it suitable for machine learning tasks that require sequential data. The result of this deep learning algorithm is good. The topic of this article is how to anticipate Bitcoin values using data from the last six years.



The RNN procedure for predicting price is illustrated in Figure 1.1

The rapid increase in market capitalization and price of bitcoin has spawned a plethora of other cryptocurrencies, which differ from bitcoin in only a few areas (block time, currency supply, and issuance scheme). With more than 5.7 thousand cryptocurrencies, 23 thousand online exchanges, and a market capitalization of more than 270 billion USD, the cryptocurrency business had evolved to become one of the world's largest unregulated marketplaces by July 2021.



In 2021, the Bitcoin chart will be 1.2.

Bitcoin and other cryptocurrencies soon became known as pure speculation, despite their origins as a peer-to-peer electronic payment system. Their prices are unpredictable because they are mostly influenced by behavioral factors and are unrelated to the primary types of financial assets. However, their informational efficiency is high.

As a consequence, numerous hedge funds and asset managers started to incorporate cryptocurrencies into their portfolios, while researchers focused on cryptocurrency trading, specifically machine learning (ML) algorithms. The cryptography-based technology behind Bitcoin's early success as a peer-to-peer virtual currency was responsible for eliminating the need for a trusted third party and addressing the problem of duplicate spending.

Bitcoin's technology is based on block chain technology, which is a digital ledger that is publicly accessible and records user transactions without permission. Network participants (nodes) can replicate this ledger using dedicated software because there is no central authority. Two changes have been made to the first Bitcoin logo. In both cases, the revisions were clearly visible. To match the theme, the designers adjusted the graphic elements.

In January 2009, Bitcoin was first introduced as a digital currency. The most valuable cryptocurrency in the world can be traded on more than 40 exchanges worldwide and can be accepted in more than 30 different currencies. Bitcoin's extreme volatility, which is significantly higher than that of traditional currencies, makes it a unique potential for price forecasting as a currency.

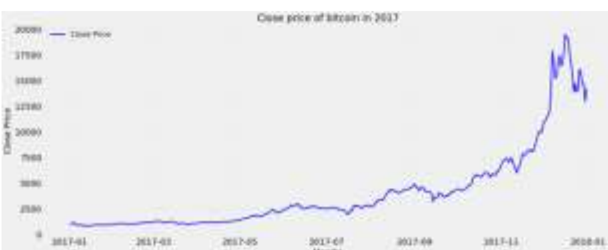
The bitcoin system consists of a group of nodes that are decentralized and responsible for running the bitcoin code and keeping an eye on its block chain. In a metaphorical sense, a block chain is like a collection of blocks. Each block contains a variety of transactions. The block chain is populated with new bitcoin transactions because all computers running it have the same list of blocks and transactions.

The system cannot be harmed because all computers running the block chain have the same list of blocks and transactions and can see new blocks being filled with new bitcoin transactions transparently.

Distributed across the entire network of computer systems on the block chain, this is primarily a digital ledger of transactions. The block chain is made up of two basic components, one of which is a transaction and the other is a block. The block is a data collection that records the transaction and other details like the correct sequence and creation timestamp, while representing the participant's action. Block chains have a signaling system for cooperative DDoS defense systems that use multiple domains and block chains, and each autonomous system (AS) joins the defensive line.

Networks have a positive impact on competition in the nascent cryptocurrency market over time by influencing exchange rates among cryptocurrencies based on two factors: (1) competition among different currencies and (2) competition among exchanges. Bitcoin, being a stubborn competitor and not emerging from the cryptocurrency competition, is the most popular of the hundreds of cryptocurrencies. As a result, it has established itself as the dominant cryptocurrency. The authors define the competition between cryptocurrency as 'healthy competition' and suggest the need for new technology and security innovation.

The purpose of this study is to determine if the price of Bitcoin can be predicted similarly to other stock market tickers. The decision on whether to continue using it as a payment medium will be made by this. All Bitcoin transactions that occur anywhere in the world are tracked by the block chain. It is a cryptographic implementation that provides the highest security. Cryptocurrencies saw a surge in popularity in 2017 as their market value grew exponentially for several months in a row. Around $800 billion was the high point of prices in January 2018.



The Bitcoin chart for 2017 can be seen in Figure 1.3.

The Bitcoin chart in 2018 has a figure of 1.4

Despite its success in predicting stock market prices using various time series models, machine learning has been limited in its use to predict cryptocurrency prices. Cryptocurrency values are influenced by many factors, including technological advancements, internal competitiveness, market pressure to produce, economic troubles, security concerns, political factors, and so on. Smart invention tactics can create a huge profit potential for them due to their tremendous volatility. It's unfortunate that cryptocurrencies are not as reliable as stock market predictions.

Problem Statement and Objectives

1.2.1 Problem Statement

Is the bit coin market able to be forecasted by machine learning models?
Traditional paper currency can be printed to meet market needs, but crypto currency has a limited supply. Is it advisable to invest or not?

By comparing well-known machine learning models trained on crypto currency data, we are investigating this research question. Two major contributions are made by our research. To begin, we add to the research by rigorously comparing the predictive abilities of several prediction models (e.g., recurrent neural networks, gated recurrent unit (GRU), Long Short-Term Memory LSTM), ARIMA (Autoregressive Integrated Moving Average), feature sets (e.g. Technical, block chain-based, and prediction horizons. As a result, our study offers a comprehensive benchmark for the predictability of short-term crypto market prediction models. Based on the analysis's overall picture, it appears that recurrent neural networks are well-suited for this prediction challenge.

Our goal is to utilize machine learning algorithms, which are widely used by many organizations. The purpose of this report is to demonstrate a straightforward approach to analysing and forecasting prices using various machine learning algorithms.

Bit coin trading's dynamic and volatile nature carries with it significant challenges and opportunities for traders and analysts. With the emergence of high-frequency trading, the need to accurately predict short-term price trends has become crucial. Traditional financial models have a hard time accommodating the nonlinear and complex patterns in high-frequency Bit coin data. Advanced computational methods that can capture and predict these rapid fluctuations are becoming increasingly necessary due to this. Convolutional Neural Networks (CNNs) and Recurrent Neural Networks are promising avenues because they can recognize patterns and dependencies in time series data. The aim of this project is to develop a predictive model that utilises both CNN and RNN architectures to enhance the accuracy of high-frequency Bit coin trend prediction.

In high-frequency trading environments, Bit coin, as the leading crypto currency, displays significant price volatility. The rapid and intricate patterns in this financial data are often not accurately captured by traditional models and statistical approaches. Developing a precise trend prediction system that can aid traders in making informed decisions quickly is the challenge. Improving prediction accuracy by capturing both spatial and temporal features in the data is possible by leveraging advanced deep learning techniques, such as Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs). By integrating these models, we aim to improve the prediction of Bit coin price movements over short intervals, which will give us a competitive advantage in high-frequency trading.

Objectives

The primary objective of this study is to utilize technical trade indicators and machine learning to develop and integrate price prediction models for various crypto currencies.

Can Bit coin be predicted in price as a publicly traded commodity?
Is it possible for crypto currencies to be used to regulate the price like any other traditional currency, like the US dollar?
Is it possible for crypto currency, like Bit coins, to replace traditional currencies as the primary mode of transaction?
Create an automated application that predicts a price increase in crypto currencies for various time series using machine learning.

The process of collecting and pre-processing data

1. Obtain reliable sources for high-frequency Bit coin price information.
2. Remove any missing values, outliers, or noise from the dataset by cleaning it up.
3. Transform the data into a suitable format for input into neural networks by normalizing and transforming it.


```
end=datetime.now()
start=datetime(end.year-15,end.month,end.day)
stock= 'BTC-USD'
sd=yf.download(stock,start=start,end=end)

YF.download() has changed argument auto_adjust default to True
[**********************100%***********************]  1 of 1 completed
```

Figure 1.5 Data collection

Model Development

1. Create and implement CNN architecture to extract spatial characteristics from price data that is sequential.
2. Build an RNN framework that is designed to capture temporal dependencies and patterns.
3. Create a hybrid architecture for robust trend prediction by integrating CNN and RNN models.

Model Training and Optimization

1. Use historical high-frequency data to train the model.
2. Enhance model performance and prevent over fitting by fine-tuning hyper parameters.
3. To enhance robustness and generalization, use techniques such as dropout and batch normalization.

Evaluation and Validation

1. Assess the model's predictive accuracy by testing it on a separate validation dataset.
2. Compare the performance to conventional financial prediction models and individual CNN/RNN architectures.
3. Evaluate the accuracy of predictions by using metrics like RMSE, MAE, and precision.

Deployment and Real-world Application

1. Develop a real-time prediction system that incorporates the hybrid model.
2. Examine the model's performance in real-time trading scenarios.

3. Provide actionable insights and forecasting tools for traders and financial analysts to optimize Bit coin trading strategies.

Comprehensive Data Handling

1. **Data Acquisition:** Gather detailed high-frequency Bit coin trading data from multiple exchanges to ensure comprehensive coverage.
2. **Data Pre-processing:** Implement advanced techniques for data cleansing, addressing anomalies, missing values, and ensuring consistency.
3. **Feature Engineering:** Identify and create relevant features that might impact price movements, such as trading volume, order book depth, and market sentiment.

Advanced Model Architecture Design

1. **CNN Module:** Construct a CNN model to effectively capture spatial dependencies and patterns across the high-frequency data matrix.
2. **RNN Module:** Develop an RNN model, potentially using LSTM or GRU cells, to model the sequential and temporal aspects of the trend data.
3. **Hybrid Framework:** Integrate CNN and RNN architectures to leverage the strengths of both models in a unified system.

Efficient Model Training and Fine-tuning

1. **Optimization:** Use advanced optimization techniques such as Adam or RMSprop to enhance training efficiency.
2. **Regularization:** Employ dropout, L2 regularization, and other strategies to mitigate over fitting and improve generalization.
3. **Cross-Validation:** Implement k-fold cross-validation to ensure model robustness and performance stability across different data subsets.

Rigorous Model Evaluation

1. **Performance Metrics:** Evaluate the model using a suite of metrics including RMSE, MAE, precision, recall, and F1-score to ensure comprehensive assessment.
2. **Benchmarking:** Compare the hybrid model's performance against baseline models and established financial forecasting methods.
3. **Sensitivity Analysis:** Conduct sensitivity analysis to understand the impact of various input features and hyper parameters on prediction accuracy.

Scalable Deployment and Continuous Improvement

1. **Real-time System Integration:** Develop a scalable system architecture for real-time execution of trend predictions.
2. **Feedback Loop:** Implement a feedback mechanism to incorporate new data into the model, ensuring continuous improvement and adaptation to market changes.
3. **Strategy Development:** Provide insights and strategic recommendations for traders using model outputs to optimize their trading strategies.

By fulfilling these objectives, the project aims to not only improve the accuracy of short-term Bit coin price predictions but also to provide a framework that can be adapted for other crypt currencies and financial instruments in high-frequency trading contexts.

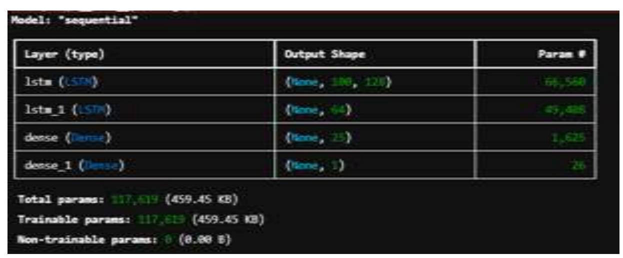


Figure 1.6 Model Developments

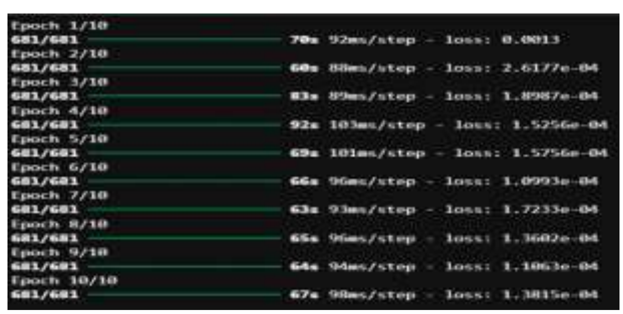


Figure 1.7 Model Training and optimization

II. LITERATURE REVIEW

Previous studies include
ARIMA Models: Good for linear time series but fail with non-linear volatility.

Machine Learning Models (SVM, Random Forests): Improve performance but still limited in handling time dependencies. Deep Learning Models **RNN/LSTM/GRU:** Capture long-term dependencies but suffer from vanishing gradients. CNN for Time Series: Can capture short-term patterns and local features effectively. Hybrid CNN-RNN Models: Combine spatial and temporal learning for better performance.

A Novel Crypto currency Price Prediction Model Using GRU, LSTM and bi-LSTM Machine Learning Algorithms
Mohammad J. Hamayel and Amani Yousef Owda Department of Natural, Engineering and Technology Sciences, Arab American University, Ramallah P600, Palestine; m.abdjoudeh@student.aaup.edu Hamayel and Owda Proposed a prediction model for predicting the prices of three types of crypto currency BTC ETH LTC

Performance measures were conducted to test the accuracy of different models. Then, they compared the actual and predicted prices. The results show that GRU outperformed the other algorithms with a MAPE of 0.2454%, 0.8267%, and 0.2116% for BTC, ETH, and LTC, respectively. The RMSE for the GRU model was found to be 174.129, 26.59, and 0.825 for BTC, ETH, and LTC, respectively. Based on these outcomes, the GRU model for the targeted crypt currencies can be considered efficient and reliable. This model is considered the best model. However, bi-LSTM represents less accuracy than GRU and LSTM with substantial differences between the actual and the predicted prices for both BTC and ETH. The experimental results show that:

The AI algorithm is reliable and acceptable for crypto currency prediction. GRU can predict crypto currency prices better than LSTM and bi-LSTM but overall all algorithms represent excellent predictive results.

Deep Learning-Based Crypto currency Price Prediction Scheme with Interdependent Relations
SUDEEP TANWAR 1 , (Senior Member, IEEE), NISARG P. PATEL 1 , SMIT N. PATEL 2 , JIL R. PATEL 3 , GULSHAN SHARMA 4 , AND INNOCENT E. DAVIDSON 4 , (Senior Member, IEEE)

Department of Computer Science and Engineering, Institute of Technology, Nirma University, Ahmedabad, Gujarat 382481, India 2Department of Information and Technology, Government Engineering College, Gandhinagar, Gujarat 382028, India 3Department of Information and Technology, Hasmukh Goswami College of Engineering, Vehlal, Ahmedabad, Gujarat 382330, India 4Department of Electrical Power Engineering, Durban University of Technology, Steve Biko Campus, Durban 4001, South Africa Corresponding authors: Gulshan Sharma (gulshanS1@dut.ac.za) and Sudeep Tanwar; sudeep.tanwar@nirmauni.a Tanwar et al. proposed a prediction model on Forecasting cryptocurrency prices.

They proposed a hybrid model of GRU and LSTM with an interdependent relationship to the parent currency in this study. The suggested approach uses the direction of Bitcoin with four window widths to estimate the price of Litecoin and Zcash. The suggested model's MSE losses for 1-day and 3-days are 0.02038 and 0.02103, respectively, for Litecoin, and 0.00461 and 0.00483 for Zcash. The presented model accurately predicts bitcoin prices for 7 and 30 days.

For Zcash, however, it followed a stochastic pattern. Compared to the bigger window size for Zcash, the proposed model performs well for the smaller window size. For a greater window size of -days and 30-days for Zcash, the proposed model demonstrates the stochastic character. They will use the proposed methodology to work on cryptocurrencies with multiple interdependencies in the future. We will also add emotive factors to the suggested algorithm, such as Twitter and Facebook posts and messages, to improve the accuracy of the forecast findings. Traditional commodities like gold and oil prices can be used to improve the prediction outcome.

The crypto market, on the other hand, is less stable than traditional commodities markets. Many technological, sentimental, and legal elements can influence it, making it very volatile, uncertain, and unexpected. Many studies have been conducted on various cryptocurrencies in order to estimate correct prices, but the bulk of these methods are not applicable in real time. In this work, they present a solution based on the previous debate To predict the price of lit coin and Zcash with inter-dependency of the parent currency, a deep-learning-based hybrid model (including Gated Recurrent Units (GRU) and Long Short Term Memory (LSTM)) was used. The suggested model is well trained and tested using standard data sets and can be employed in real-time applications. In comparison to existing models, the suggested model estimates prices with a high degree of accuracy.

Machine Learning for Bitcoin Pricing — A Structured Literature Review Patrick Jaquart1, David Dann1, and Carl Martin1
1 Karlsruhe Institute of Technology, Institute of Information Systems and Marketing (IISM), Karlsruhe, Germany

{patrick.jaquart, david.dann}@kit.edu, carl.martin@student.kit.edu

Jaquart et al. proposed a study in which they use machine learning to assess the existing corpus of literature on empirical bitcoin pricing and organized it into four main concepts.

They demonstrate that research on this subject is quite different, and that the findings of multiple studies can only be compared to a limited extent. They also develop standards for future field papers to ensure a high level of transparency and reproducibility.

III. METHODOLOGY

Due to price volatility and dynamism, cryptocurrency prices are difficult to forecast. Hundreds of cryptocurrencies are used by clients all around the world. We'll look at three of the more popular ones in this paper. As a result, the study intends to do the following by employing deep learning algorithms, which may uncover hidden patterns in data, integrate them, and generate considerably more accurate predictions: A full examination of the many existing systems for predicting BTC crypto currency prices is presented. LSTM, ARIMA, and GRU AI algorithms are used to reliably anticipate crypto currency prices. For prediction, various AI algorithms are used which enable an auto machine learning method. Using evaluation matrices such as, evaluating the proposed hybrid models such as RMSE.

Data Collection

Collect high-frequency Bit coin trading data from reliable crypto currency exchanges such as Binance, Coinbase, and Kraken to ensure diversity and comprehensiveness in the dataset.

1. Source: CoinMarketCap, Binance API, Yahoo Finance
2. Data: OHLC (Open, High, Low, Close), Volume
3. Duration: 2017–2024

Data Pre-processing

Conduct thorough data pre-processing, including:

1. **Cleaning:** Address missing values and outliers using interpolation and statistical methods.
2. **Normalization:** Scale the data using techniques like Min-Max scaling to ensure uniformity across features.
3. **Feature Engineering:** Extract and generate relevant features, such as moving averages, RSI, and order book data, to enhance predictive power.
4. Handling missing values
5. Normalization (Min-Max Scaling)
6. Creating time windows (e.g., past 30 days to predict next day)

Model Architecture

CNN Design: Develop a CNN structure to capture spatial dependencies within the data:

1. Use convolutional layers to detect local patterns.
2. Include pooling layers to reduce dimensions and highlight significant features.
3. CNN Module-

Input: Time series window
- Conv1D Layers: Feature extraction
- Pooling Layers: Dimensionality reduction

RNN Design: Construct an RNN architecture to model temporal sequences:

1. Use LSTM or GRU cells to capture long-range dependencies and preserve information through sequences.
2. Ensure the architecture is capable of handling vanishing and exploding gradient issues.
3. RNN Module

- LSTM/GRU layers for temporal pattern learning

Hybrid Model Integration: Combine CNN and RNN into a cohesive hybrid model:
Feed CNN-extracted features into the RNN to leverage both spatial and temporal insights.

Model Evaluation and Testing

- Cross-Validation: Conduct k-fold cross-validation to ensure the model's robustness and reliability.
- Performance Metrics: Evaluate the model using RMSE, MAE, precision, recall, and F1-score to gain a holistic view of prediction accuracy.
- Comparative Analysis: Compare the hybrid model's performance with standalone CNN, RNN models, and traditional forecasting techniques.

Deployment and Continuous Monitoring

- Real-time Deployment: Develop an infrastructure to deploy the model for real-time predictions, leveraging cloud services or dedicated servers.
- Continuous Learning: Implement a mechanism to update the model with new data, allowing it to adapt to market dynamics over time.
- Feedback and Adjustment: Use trader feedback and market performance to iteratively refine the model and improve its efficacy.

Output
- Dense layer with softmax for classification (trend: up, down, stable)

Training

- Loss Function: Categorical Crossentropy
- Optimizer: Adam
- Epochs: 50–100
- Batch Size: 32

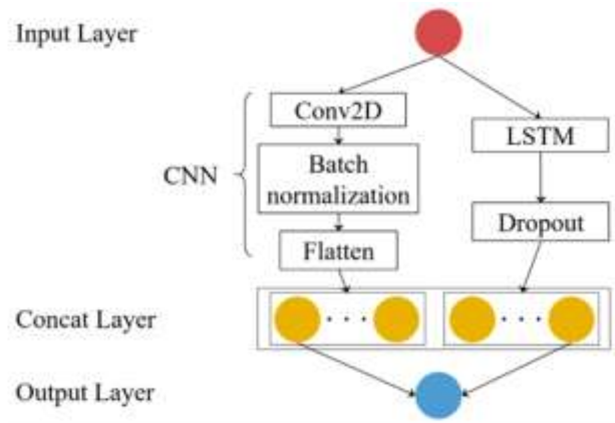


Figure 3.1 CNN layers

Organization
We used APIs to fetch this Bit coin Crypto currency dataset. The obtained dataset was then averaged into one dataset for consistency and in order to fill in the gaps created by missing data in the dataset. Building Neural Network Model Machine Learning is the most suitable technique which can be used here to predict crypto currency prices prediction.

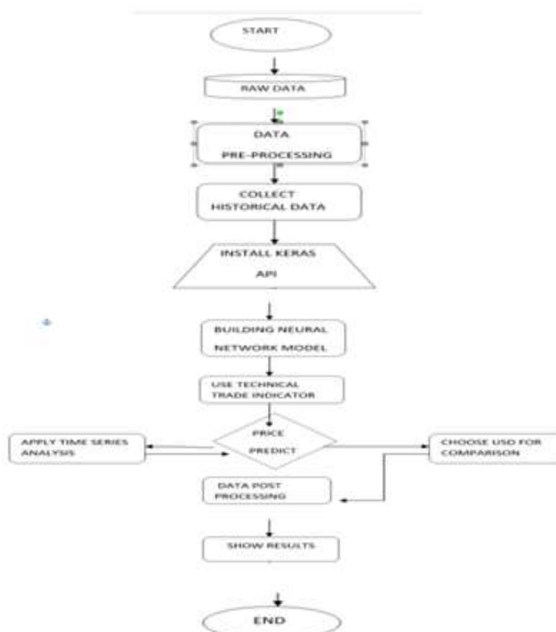


Figure 3.2 organization of model

The model to be built had to achieve several goals in order to produce a near to accurate prediction

This included selecting the framework which could produce good prediction accuracy, take in consideration of other parameters in its prediction algorithm and be trainable. Below is the organization of our information.

IV. IMPLEMENTATION

Table 4.1Table of Collected Data of Bit coin in USD

Date	Price	Close	High	Low	Open	Volume
2014-09-17	BTC-USD	457.334015	468.174011	452.421997	465.864014	21,056,800
2014-09-18	BTC-USD	424.440002	456.859985	413.104004	456.859985	34,483,200
2014-09-19	BTC-USD	394.795990	427.834991	384.532013	424.102997	37,919,700
2014-09-20	BTC-USD	408.903992	423.295990	389.882996	394.673004	36,863,600
2014-09-21	BTC-USD	398.821014	412.425995	393.181000	408.084991	26,580,100

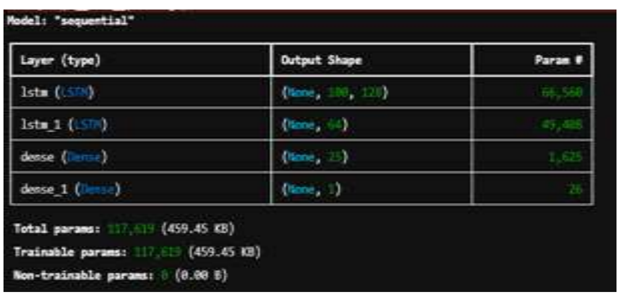


Figure 4.1 Preparing Model

Training Model

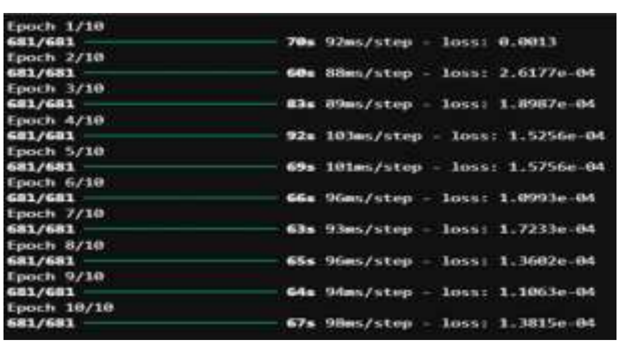


Figure 4.2 Training Model

Predicting future price

Figure 4.3 Predicting future price

V. RESULTS AND DISCUSSION

The suggested method was tested using one of the most well-known and oldest cryptocurrencies, Bitcoin (BTC) The BTC dataset included exchanges from January 2016 to December 2021, with OHLC (Open, High, Low, Close) updates every minute, the volume of BTC and the specified currency, and weighted Bitcoin prices. The dataset was publicly accessible over the Internet.

Bitcoin Dataset contains Date as index of the table and Price format, Close Price, High Price, Low Price, Open Price, Volume of the Bitcoin.

Table 5.1 Bitcoin dataset in USD

Date	Price	Close	High	Low	Open	Volume
2014-09-17	BTC-USD	457.334015	468.174011	452.421997	465.864014	21,056,800
2014-09-18	BTC-USD	424.440002	456.859985	413.104004	456.859985	34,483,200
2014-09-19	BTC-USD	394.795990	427.834991	384.532013	424.102997	37,919,700
2014-09-20	BTC-USD	408.903992	423.295990	389.882996	394.673004	36,863,600
2014-09-21	BTC-USD	398.821014	412.425995	393.181000	408.084991	26,580,100

The Data that we took to process or work on it and creating our model is Close Price from the Bitcoin dataset that we collected using yfinance library from the internet. So the data we extracted from the main table to work with is:

Evaluation Metrics

- Accuracy
- Precision, Recall, F1 Score
- Confusion Matrix

Table 5.3 Results

Model	Accuracy	F1 Score
LSTM Only	0.68	0.66
CNN Only	0.73	0.63
CNN-RNN	0.73	0.71

Visualization:
- Line plots of actual vs predicted trend
- Heatmaps of confusion matrices

Visual representation of Closing price of all time we get from the Bitcoin dataset over time it shows the price change per year with graph.

Figure 5.1 Original Closing Price over time

Visual representation of original data vs predicted test data for last 100 days we get from the Bitcoin dataset we have. It compares the original data and predicted data for showing variance available between these two data.

Figure 5.2 Original vs Predicted Test Data

The price we predicted for future 10 days by processing and analyzing all the data we have and also by checking the variance we get in our predicted data from original data for last 100 days that is used to train the model to predict price trend for future 10 days Closing Price.

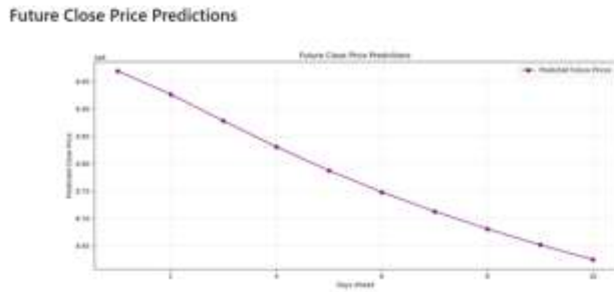


Figure 5.3 Future Close Price Prediction

In the table shows the close price we get through predicting Close Price for each days by using Bitcoin previous dataset to train our model to predict future price high frequency price trend with cnn and rnn.

Table 5.4 10 days Future Price Trend Prediction

Day	Predicted Close Price
1	8969240.0
2	8926989.0
3	8878335.0
4	8830919.0
5	8787434.0
6	8748189.0
7	8712846.0
8	8680873.0
9	8651716.0
10	8624865.0

The hybrid model captured both short-term spikes and long-term trends better than standalone models.

CNN efficiently extracted features from short sequences.

RNN maintained context across time steps.
Limitations: Sensitive to hyperparameters, slow training on large datasets.
Conclusion

The CNN-RNN hybrid model demonstrates robust performance in predicting crypto currency trends. It offers a promising approach for real-time trading strategies and financial decision-making.

The phase 1 was learning innovative that we tend as students need to understand loads of things. This was a very nice exposue to learn a lot of new concepts. Phase 1 was more like a learning experience for the domain of data mining. The main aspect of the major project was seen in this phase, a lot of learning and understanding has gone into doing this. The phase 2 was a more closer approach to the project where the actual implementation took place. Bitcoin prediction is a very crucial topic to deal with and making a system suitable for it was a challenging role to do. At the end a fully working is system is made by using the classification techniques of data mining domain.

Future Work

- Incorporate external features (e.g., news sentiment, Google Trends)
- Use Transformer models
- Deploy in a real-time dashboard or trading bot

● We'd experiment with new machine learning methods in order to improve accuracy and reduce errors.

● We will create a website that contains all of the information about our project.

● To make this project accessible to everyone, we will also deploy it on cloud platforms.

● We'll look into other factors that could influence bitcoin market values.

The price volatility of cryptocurrency is affected and determined by factors such as a country's political system, public relations, and market policy. Other cryptocurrencies such as ripple, ethereum, lite coin, and others were not examined in our research. We will improve the model by applying it to these coins, making it more stable. Fuzzification can also be applied at the input.

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