CRYPTOCURRENCY TREND ANALYSER AND RECOMMENDATION SYSTEM USING DEEP LEARNING

Project report submitted in fulfilment of the requirement for the degree of Bachelor of Technology
in

Computer Science and Engineering

By

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Under the supervision of

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to

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Certificate

We hereby declare that the work presented in this report entitled **Cryptocurrency Trend Analyser and Recommendation System using Deep Learning** in partial fulfilment of the requirements for the award of the degree of **Bachelor of Technology** in **Computer Science and Engineering** submitted in the department of Computer Science & Engineering and Information Technology, Jaypee University of Information Technology Waknaghat is an authentic record of my own work carried out over a period from January 2023 to May 2023 under the supervision of Dr. Rakesh Kumar Bajaj, Professor and HOD, Mathematics Department & Mr. Prateek Thakral, Assistant Professor, Department of Computer Science and Engineering, Jaypee University of Information Technology, Waknaghat.

I also authenticate that I have carried out the above mentioned project work under the proficiency stream Data Science.

The matter embodied in the report has not been submitted for the award of any other degree or diploma.

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This is to certify that the above statement made by the candidate is true to the best of my knowledge.

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Paras Sharma (191256)

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Table of Contents

List of Abbreviations

Sr. No.	Abbreviation	Full Form
1	BTC	Bitcoin
2	ETH	Ethereum
3	SOL	Solana
4	DOGE	Dogecoin
5	ADA	Cardano
6	S&R	Support and Resistance
7	RNN	Recurrent Neural Networks
8	NN	Neural Networks
9	ARIMA	Autoregressive Integrated Moving Average
10	LSTM	Long Short Moving Average
11	BNN	Bayesian Neural Networks

List of Figures

List of Tables

Abstract

Cryptocurrencies are blockchain based digital currencies and have many applications in today's world, cryptocurrencies are being accepted as a form of money in many countries. Cryptocurrencies can be traded on many exchanges and traders can benefit from trading by predicting on the right time about the possible trend of the cryptocurrency. The skill of trading requires a lot of knowledge about technical analysis and fundamental analysis. A trader should be able to time the market based on the sentiments and mood of the market and based on the prediction, an estimate of how the particular cryptocurrency can perform in the market can be formed.

This project intends to make trading of cryptocurrencies easier using deep learning and machine learning techniques. First of all five cryptocurrencies,viz. Bitcoin(BTC), Litecoin(LTC), Solana(SOL), Dogecoin(DOGE) and Ethereum(ETH) are selected and datasets of all of those five are considered, downloaded from kaggle. The datasets contain historical time series data. After cleaning and preprocessing of the datasets of all the five cryptocurrency datasets, all of the datasets are split into training and testing sub datasets.

Different machine learning and deep learning models are created and trained with the five sub datasets for training. After testing all the datasets on the models, a comparative analysis is performed on the models and the best model is chosen for which the models give best accuracy.

In the end a twitter sentiment analysis is performed on the basis of various tweets of the users and the market sentiment gives a clear idea about the market analysis. On the basis of the prediction given by the deep learning model and the twitter sentiment analysis model, the user can easily identify the trend of the market.

Chapter 1 Introduction

1.1 Introduction

Cryptocurrencies are blockchain based currencies which have got many applications today. In 1983, American cryptographer David Chaum created a kind of scrambled electronic cash called ecash. Then, in 1995, he executed an early type of cryptographic electronic instalment, he carried out through Digicash. Digicash expects the client of his product to pull the bill from the bank and decide the particular encryption key prior to sending the bill to the payee. Thus, computerised money couldn't be followed by outsiders.

In 1996, the public safety Office distributed a paper named How to Fabricate a Mint. Unknown electronic cash cryptography that depicts the digital money framework. This paper originally showed up on the MIT mailing rundown and afterward in 1997 in The American Regulation Audit.

In their 1997 book The Sovereign Individual, writers William Rees-Mogg and James Dale Davidson anticipated that the monetary standards utilised in the data age would utilise numerical calculazIn

In June 2021, El Salvador turned into the first to acknowledge Bitcoin as legitimate delicate after the Official Gathering casted a ballot 62 to 22 against him to pass a bill presented by Guileless President Bukele to group digital forms of money thusly.
In August 2021, Cuba perceived and controlled digital currencies, for example, Bitcoin following Goal 215. In September 2021, the Chinese government, the biggest single digital currency market, declared all cryptographic money exchanges unlawful. This finishes a crackdown on digital currencies that recently precluded middle people and excavators from working in China.
On September 15, 2022, Ethereum, then the world's second biggest cryptographic money, changed its agreement component from Verification of Work (PoW) to Evidence of Stake (PoS) in an overhaul cycle known as 'consolidating'. . As per Ethereum's organisers, this redesign will decrease Ethereum's energy utilization by 99.9% and its carbon impression by 99.9%. Blockchain is a vital solution to decentralisation and cryptocurrencies are decentralised currencies which are not regulated by any authority, rather it is owned and used by people. Cryptocurrencies can also be mined by miners and thus mint new currencies. Cryptocurrencies got into trend less than two decades ago and now some businesses and people also accept cryptocurrencies instead of money. Cryptocurrencies are also considered as assets on the basis of their uptrend for so many years, on that account cryptocurrencies are used as a trading entity by many traders worldwide. Due to the high volatility and price fluctuations, cryptocurrencies may be considered as a risky entity to trade with. High price fluctuations are common in cryptocurrencies and its volatility makes it difficult to predict the possible direction of the price. Mainly cryptocurrencies got into light after 2013, though it is totally different from traditional money, many countries have started accepting a few cryptocurrencies in lieu of money. Some major companies have started accepting cryptocurrencies as a method to buy their services and products. Some projects like Cardano are really contributing to society. Cardano’s blockchain technology is used by the Ethiopian government to provide education to children by providing them with digital grade verification using Cardano’s blockchain technology. Another cryptocurrency, Ethereum is used by many computer science and blockchain engineers and companies to develop blockchain technologies all over the world. As blockchain technology is fairly transparent and is nearly impossible to temper with the record of once feeded, blockchain technology is the future of the world and it is going to be used widely in many real-world applications starting from educating children to conducting government elections. As of today, there are thousands of cryptocurrencies which are regularly launched under several projects and some of them have the potential to bring a change in the world and serve a purpose. The most

famous of all cryptocurrencies and one of the oldest is Bitcoin (BTC), invented in 2009 by an anonymous person named Satoshi Nakamoto, bitcoins are the most traded of all the cryptocurrencies. Others include Ethereum (ETH), which is also a decentralised blockchain based currency, Ethereum's blockchain technology is used widely in projects and real-world applications. Other cryptocurrencies like Cardano (ADA), Litecoin (LTC), Solana (SOL) are also on the boom and are traded worldwide.

The blockchain offers information about each cryptocurrency coin's legitimacy. A blockchain is a growing set of documents, or blocks, that are connected and secured via encryption. A timestamp, a hash pointer, and transaction information tying each block to the one before it are usually present in each block. Blockchains are tolerant of data changes by nature. It is an open distributed ledger that enables effective, verifiable, and durable recording of transactions between two parties. Blockchains are often controlled by peer-to-peer networks that collectively follow a system for validating new blocks in order to function as a distributed ledger. Once recorded, the information contained within a block cannot be changed in the past without also altering all blocks that follow, necessitating network-wide cooperation.

Blockchain is an illustration of a distributed computing system that has a high level of Byzantine fault tolerance and is intrinsically secure. Blockchain has therefore attained decentralised consensus.

A machine that joins a cryptocurrency network is called a node. The node helps the bitcoin network by relaying transactions, validating them, or hosting a copy of the blockchain. Each network computer (node), in terms of relaying transactions, has a copy of the blockchain of the cryptocurrency it supports. When a transaction is made, the node that made it broadcasts the transaction's specifics to other nodes across the node network using encryption, making sure that the transaction and all others are known.

Node owners can be either volunteers, those hosted by the entity in charge of creating the bitcoin blockchain network technology, or those who host a node in exchange for benefits from the node network.

To prove the legitimacy of transactions uploaded to the blockchain ledger without the requirement for a reliable third party, cryptocurrencies use a variety of timestamping systems. The proof-of-work method was the first stamping technique developed. Based on SHA-256 and script, the most popular proof-of-work algorithms are utilised. X11, CryptoNight, Blake, SHA-3, and other hashing algorithms are also used for proof of work.

Proof of Stake is still another technique. By requiring users to demonstrate ownership of a certain amount of money, Proof-of-Stake is a technique for securing a cryptocurrency network and achieving decentralised consensus. Unlike proof-of-work systems, which use complex hashing techniques to validate digital transactions There is presently no standard format for the system, which is significantly dependent on currencies. The proof-of-work and proof-of-stake algorithms are combined in some cryptocurrencies.

In the early years, due to unavailability of complete data and less visualisation tools, it was not feasible to build a model to predict the prices, with the advancements of tools and technologies like machine learning and deep learning, it has become a lot easier to predict the values of the assets. Many researchers have worked in this field and made models which can predict the future values of cryptocurrencies using different techniques. A lot of research work has been done in this field, the cryptocurrency industry has been on boom since 2015 and various new technologies like web3, metaverse, NFTs are built on the basis of these technologies. Thus cryptocurrency is a matter of interest of many researchers, especially in the field of trading.

Compared to reputable financial assets like equities, cryptocurrency prices are significantly more volatile. For instance, in the same week in May 2022, the value of Bitcoin dropped by 20%, that of Ethereum by 26%, and that of Solana and Cardano by 41% and 35%, respectively. Warnings about inflation were the cause of the fall. In contrast, the FTSE 100 dropped 3.6% and the Nasdaq technology stock index dropped 7.6% during the same week.

In the long run, just four of the top 10 cryptocurrencies—Bitcoin, Ethereum, Cardano, and Ripple (XRP)—that were ranked by the total number of coins in circulation in January 2018 will still be in use in the first few months of 2022. stayed in this place. At the end of 2021, the total market value of all cryptocurrencies was $2 trillion, but this value had been cut in half nine months later. The Wall Street Journal remarked that because the cryptocurrency industry is interconnected with other capital markets, it is susceptible to the same forces driving tech stocks and other risky assets, such as inflation expectations.

A cryptocurrency exchange or digital currency exchange is a company that enables consumers to swap cryptocurrencies or digital currencies for other assets like traditional fiat currencies and other digital currencies. For the trading of digital assets or cryptocurrencies, exchanges might accept credit card payments, wire transfers, or other payment options. Exchanges for cryptocurrencies may act as market makers in this case, they typically collect trading commissions from bid-ask spreads or merely charge fees for acting as a matching service.

Users can buy cryptocurrencies from some brokers, like Robinhood and eToro, which also concentrate on other assets like stocks, but they are unable to withdraw them into their cryptocurrency wallets. On the other hand, withdrawals of cryptocurrencies are permitted on specific exchanges like Binance and Coinbase.

A cryptocurrency exchange or digital currency exchange is a company that enables clients to swap cryptocurrencies or digital currencies for other assets like conventional fiat currencies and other digital currencies. Cryptocurrencies can be transferred from exchanges to a user's private cryptocurrency wallet. Some are backed by tangible assets like gold, while others can convert digital currency balances into anonymous prepaid cards that can be used to withdraw cash from ATMs all over the world.

The exchanges that enable the trading of digital currencies are frequently not affiliated with the currencies' creators. A Digital Currency Provider is a business that handles and administers accounts for its clients but does not frequently issue digital currency to them directly in this type of system. A customer buys and sells digital currency from an exchange that transfers digital currency to and from the customer's Digital Currency Provider account. A few exchanges are Digital Currency Provider subsidiaries, but the majority are independent businesses. The amount of money stored in a Digital Currency Provider Account may be expressed in either real money or digital money.

Whether it operates offline or solely online, a digital currency exchange can exist. It accepts both conventional payment methods and virtual currencies because it is an actual store. As an online company, we trade digital currency for electronically transmitted funds. In order to evade regulation and prosecution, digital currency exchangers frequently operate outside of Western nations. However, it manages bank accounts across several nations to accept deposits made in different local currencies, handles western fiat currencies, and manages bank accounts.

Peer-to-peer cryptocurrency trading is made possible via decentralised exchanges like Etherdelta, IDEX, and HADAX, as opposed to the exchanges' own centralised storage of user cash. Although decentralised exchanges can withstand security problems that strike traditional exchanges, trade volumes have been declining since mid-2018. Exchanges for cryptocurrencies can act as market makers, often collecting trading commissions from bid-ask spreads or just charging fees for acting as a matching service. Users can buy cryptocurrencies via some brokers, like Robinhood and eToro, who also specialise on other assets like stocks, but they are unable to withdraw them into their cryptocurrency wallets. On the other hand, withdrawals of cryptocurrencies are permitted on specific exchanges like Binance and Coinbase.

A cryptocurrency exchange or digital currency exchange is a business that allows customers to exchange cryptocurrencies or digital currencies for other assets such as traditional fiat currencies and other digital currencies. Exchanges can send cryptocurrencies to a user's personal cryptocurrency wallet. Some can convert digital currency balances into anonymous prepaid cards that can be used to withdraw money from ATMs around the world, while others are backed by physical commodities like gold.

The exchanges that enable the trading of digital currencies are frequently not affiliated with the currencies' creators. A corporation that stores and administers accounts for its clients but does not normally distribute digital currency to them directly is referred to as a Digital Currency Provider in this sort of system. A consumer buys and sells digital currency from a digital currency exchange that sends and receives digital currency to and from the customer's digital currency provider account. Although many exchanges are independent legal businesses, some are subsidiaries of the digital currency provider. Funds held in a Digital Currency Provider Account may be denominated in real or digital money.

Whether it operates offline or solely online, a digital currency exchange can exist. It accepts both conventional payment methods and virtual currencies because it is an actual business. As an online company, we trade digital currency for electronically transmitted funds. In many situations, digital currency exchanges operate outside of Western nations to escape regulation and punishment. However, it manages bank accounts across several nations to accept deposits made in different local currencies, handles western fiat currencies, and manages bank accounts.

Peer-to-peer cryptocurrency trading is made possible via decentralised exchanges like Etherdelta, IDEX, and HADAX rather than by holding user money on exchanges. Although decentralised exchanges are resilient to security problems affecting other exchanges, trading volumes have decreased since mid-2018. It is possible to advertise cryptocurrency exchanges. His three digital currency exchanges in Australia were voluntarily shut down in 2004 as a result of an Australian Securities and Investments Commission inquiry. The firm lacked an Australian financial services licence, which ASIC considered was legally needed for the services being supplied.

After running a digital currency exchange and money transfer company out of their home since 2002, New York-based Gold Age Inc. was shut down by American intelligence authorities in 2006. 30 multi-million dollar digital currency accounts. A rice field. Customers were allowed to transfer money to anybody in the globe with only a minimal amount of identification and fees that occasionally exceeded $100,000. Licence, breach of state banking rules, and received a five-year probationary term as a result. About 58 e-gold accounts belonging to The Bullion Exchange, AnyGoldNow, IceGold, GitGold, The Denver Gold Exchange, GoldPouch Express, and 1MDC were allowed to operate under the e-gold administration, the U.S. government announced in April 2007. ordered to be stopped or frozen. used to support e-gold and other services, owners of OmniPay had to sell their confiscated assets.

WebMoney modified its policies in July 2008, which had an impact on numerous exchanges. Since that time, it is prohibited to exchange WebMoney for the most widely used digital currencies, including e-gold and Liberty Reserve.

1.2 Problem Statement

The widespread adoption of cryptocurrencies has transformed the traditional financial ecosystem, giving rise to a new era of decentralised and trustless transactions. However, with the proliferation of hundreds of cryptocurrencies, each with its unique features, it becomes challenging for investors and traders to keep track of the changing market trends and make informed decisions. This is where a Cryptocurrency Trend Analyser and Recommendation System using Deep Learning can be useful.

The next step involves developing a deep learning model that can predict the price trends of various cryptocurrencies. The system uses various deep learning algorithms such as Long Short-Term Memory (LSTM), Recurrent Neural Networks (RNNs), and Convolutional Neural Networks (CNNs) to analyse the data and generate predictions. The deep learning model takes into account various factors such as the historical prices, trading volumes, market capitalization, and other relevant indicators to generate accurate predictions.

1.3 Objectives

The project "Cryptocurrency Trend Analyser and Recommendation System using Deep Learning" aims to develop a system that can analyse the trends of different cryptocurrencies and provide investment recommendations to users. Deep learning algorithms will be used to process and analyse large amounts of data related to different cryptocurrencies, including historical price data and social media sentiment.

The project's analysis of historical pricing data for several cryptocurrencies will look for trends and patterns. Predictive models can be created using this data to assist users in choosing investments. The algorithm can predict likely future trends by examining past price movements and can then provide recommendations based on this information.

Analysis of social media sentiment on various cryptocurrencies is the third goal. Cryptocurrency prices can be significantly influenced by social media. The system should be able to evaluate user sentiment on social media and use this data to spot prospective pricing changes. The technology can offer a more complete picture of the bitcoin market and make more precise investment suggestions by studying social media opinion.
The fifth goal is to create predictive models using sentiment analysis of social media and historical pricing data. Users may receive investing advice from these models. The technology can create more precise forecast models and offer more knowledgeable investment suggestions by employing deep learning algorithms to examine massive volumes of data.

The creation of investment suggestions for consumers based on data analysis and the creation of prediction models is the sixth goal. These suggestions must be made in an approachable manner and should be customised to the user's investment profile. The technology can assist users in choosing investments that are suited for their financial goals and risk tolerance by offering customised investment recommendations.

The "Cryptocurrency Trend Analyser and Recommendation System using Deep Learning" project's goals are to create a system that can evaluate the trends of various cryptocurrencies and make investment suggestions to users. By fulfilling these goals, the system will be able to assist users in selecting wise investments and navigating the complicated world of bitcoin trading.

1.4 Methodology

This proposed method as shown in Figure 1 shows the use of linear regression model and Bayesian model on the same cryptocurrency dataset and then comparatively analysing the results of both the models and picking the best and optimised model. Different cryptocurrency datasets are used for both of the models for versatility and avoiding overfitting and underfitting. This proposed methodology starts with A. Picking up the dataset followed by B. visualising the dataset and printing its original values. Further C. Linear Regression is applied over each dataset followed by the D. Bayesian Model also on each dataset of the cryptocurrencies. E. Comparative analysis is performed on the results of both the models and the best and optimal model is chosen and the final results are explored.

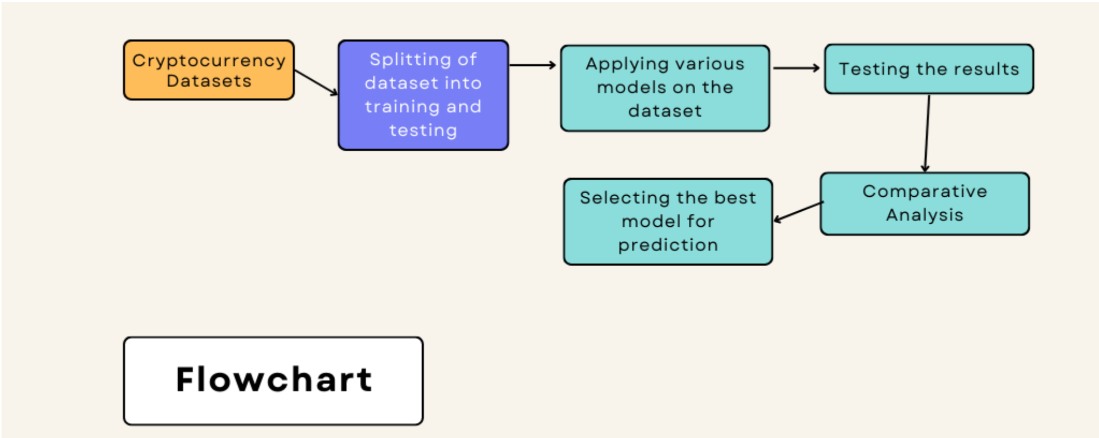


Fig. 1.1: Proposed Methodology

A. The datasets of five different cryptocurrencies, namely, Bitcoin (BTC), Etherium (ETH), Litecoin (LTC), Cardano (ADA), Solana (SOL) and Dogecoin (DOGE) are used here which are taken from Kaggle. The time frame for the Dataset is starting from 2013 and ending in 2021. The dataset contains Opening price, i.e. the initial price of the crypto currency on the particular day, Closing Price, i.e. the last price of the crypto currency on the particular day at which it traded, High Price, i.e. the highest price of the crypto currency at which it traded on the particular day, Low Price, i.e. the lowest price of the crypto currency at which it traded on the particular day, for every day for all these years. The dataset also contains the volume, i.e. the no. of crypto currency coins traded on the particular day for all the days for all the years.

B. First of all the data set is stored in a dataframe using the pandas library in python as shown in figure 2. The figure shows the various features of the dataset as discussed above. The figure 2 shows the dataset of ‘Bitcoin’

	SNo	Name	Symbol	Date	High	Low	Open	Close	Volume	Marketcap
0	1	Bitcoin	BTC	2013-04-29 23:59:59	147.488007	134.000000	134.444000	144.539993	0.000000e+00	1.603769e+09
1	2	Bitcoin	BTC	2013-04-30 23:59:59	146.929993	134.050003	144.000000	139.000000	0.000000e+00	1.542813e+09
2	3	Bitcoin	BTC	2013-05-01 23:59:59	139.889999	107.720001	139.000000	116.989998	0.000000e+00	1.298955e+09
3	4	Bitcoin	BTC	2013-05-02 23:59:59	125.599998	92.281898	116.379997	105.209999	0.000000e+00	1.168517e+09
4	5	Bitcoin	BTC	2013-05-03 23:59:59	108.127998	79.099998	106.250000	97.750000	0.000000e+00	1.085995e+09
...	...	...	...	...	...	...	...	...	...	...
2986	2987	Bitcoin	BTC	2021-07-02 23:59:59	33939.588699	32770.680780	33549.600177	33897.048590	3.872897e+10	6.354508e+11
2987	2988	Bitcoin	BTC	2021-07-03 23:59:59	34909.259899	33402.696536	33854.421362	34668.548402	2.438396e+10	6.499397e+11
2988	2989	Bitcoin	BTC	2021-07-04 23:59:59	35937.567147	34396.477458	34665.564866	35287.779766	2.492431e+10	6.615748e+11
2989	2990	Bitcoin	BTC	2021-07-05 23:59:59	35284.344430	33213.661034	35284.344430	33746.002456	2.672155e+10	6.326962e+11
2990	2991	Bitcoin	BTC	2021-07-06 23:59:59	35038.536363	33599.916169	33723.509655	34235.193451	2.650126e+10	6.418992e+11

2991 rows × 10 columns

Fig. 1.2 BTC Data

We have used a total of six cryptocurrencies for the purpose of training and testing of the models we have applied. The figure 3 shows the Ethereum dataset. Ethereum is a very recent and very famous cryptocurrency, it is based on decentralised blockchain technology and has many applications in the field of blockchain technology, many projects based on blockchain are based on ethereum.

	SNo	Name	Symbol	Date	High	Low	Open	Close	Volume	Marketcap
0	1	Ethereum	ETH	2015-08-08 23:59:59	2.798810	0.714725	2.793760	0.753325	6.741880e+05	4.548689e+07
1	2	Ethereum	ETH	2015-08-09 23:59:59	0.879810	0.629191	0.706136	0.701897	5.321700e+05	4.239957e+07
2	3	Ethereum	ETH	2015-08-10 23:59:59	0.729854	0.636546	0.713989	0.708448	4.052830e+05	4.281836e+07
3	4	Ethereum	ETH	2015-08-11 23:59:59	1.131410	0.663235	0.708087	1.067860	1.463100e+06	6.456929e+07
4	5	Ethereum	ETH	2015-08-12 23:59:59	1.289940	0.883608	1.058750	1.217440	2.150620e+06	7.364501e+07
...	...	...	...	...	...	...	...	...	...	...
2155	2156	Ethereum	ETH	2021-07-02 23:59:59	2155.596496	2021.824808	2109.892677	2150.040364	3.179621e+10	2.505527e+11
2156	2157	Ethereum	ETH	2021-07-03 23:59:59	2237.567155	2117.590013	2150.835025	2226.114282	1.743336e+10	2.594475e+11
2157	2158	Ethereum	ETH	2021-07-04 23:59:59	2384.286857	2190.837703	2226.550382	2321.724112	1.878711e+10	2.706217e+11
2158	2159	Ethereum	ETH	2021-07-05 23:59:59	2321.922836	2163.041394	2321.922836	2198.582464	2.010379e+10	2.562978e+11
2159	2160	Ethereum	ETH	2021-07-06 23:59:59	2346.294874	2197.919385	2197.919385	2324.679449	2.089186e+10	2.710286e+11

2160 rows × 10 columns

Fig. 1.3 ETH Data

Cardano(ADA) is another very recent and very widely used cryptocurrency which is also based on the concept of blockchain. Cardano has many applications also in healthcare and is used by many governments also for many purposes. Cardano is decentralised as well as it is open to use. Figure 4 shows the cardano dataset.

	SNo	Name	Symbol	Date	High	Low	Open	Close	Volume	Marketcap
0	1	Cardano	ADA	2017-10-02 23:59:59	0.030088	0.019969	0.024607	0.025932	5.764130e+07	6.288991e+08
1	2	Cardano	ADA	2017-10-03 23:59:59	0.027425	0.020690	0.025757	0.020816	1.699780e+07	5.396927e+08
2	3	Cardano	ADA	2017-10-04 23:59:59	0.022806	0.020864	0.020864	0.021931	9.000050e+06	5.686195e+08
3	4	Cardano	ADA	2017-10-05 23:59:59	0.022154	0.020859	0.021951	0.021489	5.562510e+06	5.571390e+08
4	5	Cardano	ADA	2017-10-06 23:59:59	0.021542	0.018360	0.021359	0.018539	7.780710e+06	4.806646e+08
...	...	...	...	...	...	...	...	...	...	...
1369	1370	Cardano	ADA	2021-07-02 23:59:59	1.394397	1.286607	1.332942	1.394397	2.159410e+09	4.454587e+10
1370	1371	Cardano	ADA	2021-07-03 23:59:59	1.441714	1.359664	1.394152	1.406836	2.028094e+09	4.494324e+10
1371	1372	Cardano	ADA	2021-07-04 23:59:59	1.493717	1.382153	1.404008	1.458184	1.806362e+09	4.658364e+10
1372	1373	Cardano	ADA	2021-07-05 23:59:59	1.461221	1.379284	1.461221	1.404898	1.759461e+09	4.488134e+10
1373	1374	Cardano	ADA	2021-07-06 23:59:59	1.456887	1.393282	1.404712	1.418053	1.477700e+09	4.530158e+10

1374 rows × 10 columns

Fig. 1.4 ADA Dataset

Dogecoin(DOGE) is another cryptocurrency which was initially started as a joke. It was never intended to be a proper cryptocurrency like the other cryptocurrencies like Bitcoin(BTC), Ethereum(ETH), Cardano(ADA). It was just an experimental cryptocurrency and was intended for fun, but later when people started to trade in it and took it seriously in 2020, it gave exceptionally high returns to its investors and traders. Since then, it has been in trend and traders are keeping a watch on this cryptocurrency as well.

	SNo	Name	Symbol	Date	High	Low	Open	Close	Volume	Marketcap
0	1	Dogecoin	DOGE	2013-12-16 23:59:59	0.000866	0.000150	0.000299	0.000205	0.000000e+00	1.509085e+06
1	2	Dogecoin	DOGE	2013-12-17 23:59:59	0.000289	0.000116	0.000207	0.000269	0.000000e+00	2.169688e+06
2	3	Dogecoin	DOGE	2013-12-18 23:59:59	0.000362	0.000205	0.000267	0.000362	0.000000e+00	3.188943e+06
3	4	Dogecoin	DOGE	2013-12-19 23:59:59	0.001520	0.000328	0.000395	0.001162	0.000000e+00	1.115034e+07
4	5	Dogecoin	DOGE	2013-12-20 23:59:59	0.001143	0.000662	0.001143	0.000704	0.000000e+00	7.284337e+06
...	...	...	...	...	...	...	...	...	...	...
2755	2756	Dogecoin	DOGE	2021-07-02 23:59:59	0.247997	0.238848	0.243982	0.245264	1.321471e+09	3.194925e+10
2756	2757	Dogecoin	DOGE	2021-07-03 23:59:59	0.250214	0.242454	0.245106	0.246411	9.170158e+08	3.210491e+10
2757	2758	Dogecoin	DOGE	2021-07-04 23:59:59	0.252567	0.243425	0.246425	0.246483	9.735115e+08	3.211767e+10
2758	2759	Dogecoin	DOGE	2021-07-05 23:59:59	0.246419	0.227838	0.246419	0.231614	1.267949e+09	3.018344e+10
2759	2760	Dogecoin	DOGE	2021-07-06 23:59:59	0.241910	0.229842	0.231216	0.234422	1.265920e+09	3.055252e+10

2760 rows × 10 columns

Fig. 1.5: DOGE Dataset

Yet another cryptocurrency is Solana, which is also a decentralised and blockchain based technology, we have considered Solana in our project. The tabular dataset of Solana which contains the historical values of the cryptocurrency in a time series format is shown in the figure below.

	SNo	Name	Symbol	Date	High	Low	Open	Close	Volume	Marketcap
0	1	Solana	SOL	2020-04-11 23:59:59	1.049073	0.765020	0.951054	0.776819	4.386244e+07	0.000000e+00
1	2	Solana	SOL	2020-04-12 23:59:59	0.956670	0.762426	0.785448	0.882507	3.873690e+07	0.000000e+00
2	3	Solana	SOL	2020-04-13 23:59:59	0.891603	0.773976	0.890760	0.777832	1.821129e+07	0.000000e+00
3	4	Solana	SOL	2020-04-14 23:59:59	0.796472	0.628169	0.777832	0.661925	1.674761e+07	0.000000e+00
4	5	Solana	SOL	2020-04-15 23:59:59	0.704964	0.621531	0.669289	0.646651	1.307528e+07	0.000000e+00
...	...	...	...	...	...	...	...	...	...	...
447	448	Solana	SOL	2021-07-02 23:59:59	34.031786	31.479924	33.306310	34.020482	4.402988e+08	9.275257e+09
448	449	Solana	SOL	2021-07-03 23:59:59	35.404770	33.298475	34.015575	34.478816	3.270200e+08	9.400216e+09
449	450	Solana	SOL	2021-07-04 23:59:59	35.502372	33.555737	34.495117	34.310601	3.034205e+08	9.354354e+09
450	451	Solana	SOL	2021-07-05 23:59:59	34.461824	32.482692	34.282550	32.984588	3.138393e+08	8.992833e+09
451	452	Solana	SOL	2021-07-06 23:59:59	34.978319	32.930307	32.930307	34.269140	3.653360e+08	9.343050e+09

452 rows × 10 columns

Fig. 1.6: SOL Dataset

The sixth cryptocurrency used in this project is Litecoin, in the trend of cryptocurrencies, there are many cryptocurrencies which are being launched and it is estimated that around twenty new cryptocurrencies are launched every day. This boom of cryptocurrency came in 2020. With this many new cryptocurrency launches everyday, it is very essential for traders to keep track of the major cryptocurrencies and litecoin is one of them. Litecoin is a blockchain based and decentralized cryptocurrency listed on many cryptocurrency exchanges. The tabular dataset of Litecoin which contains the historical values of the cryptocurrency in a time series format is shown in the figure below.

	SNo	Name	Symbol	Date	High	Low	Open	Close	Volume	Marketcap
0	1	Litecoin	LTC	2013-04-29 23:59:59	4.573600	4.225640	4.366760	4.383900	0.000000e+00	7.538896e+07
1	2	Litecoin	LTC	2013-04-30 23:59:59	4.572380	4.168960	4.403520	4.296490	0.000000e+00	7.402092e+07
2	3	Litecoin	LTC	2013-05-01 23:59:59	4.356860	3.520290	4.289540	3.801010	0.000000e+00	6.560460e+07
3	4	Litecoin	LTC	2013-05-02 23:59:59	4.039300	3.007170	3.780020	3.371980	0.000000e+00	5.828798e+07
4	5	Litecoin	LTC	2013-05-03 23:59:59	3.453610	2.395940	3.390440	3.044910	0.000000e+00	5.269485e+07
...	...	...	...	...	...	...	...	...	...	...
2986	2987	Litecoin	LTC	2021-07-02 23:59:59	138.787700	130.935471	137.299274	136.943696	1.418981e+09	9.141322e+09
2987	2988	Litecoin	LTC	2021-07-03 23:59:59	141.356011	134.945288	136.930584	140.279688	1.236494e+09	9.364008e+09
2988	2989	Litecoin	LTC	2021-07-04 23:59:59	147.836059	137.096427	140.317998	144.905849	1.431657e+09	9.672815e+09
2989	2990	Litecoin	LTC	2021-07-05 23:59:59	144.849333	134.960263	144.849333	138.073246	1.338246e+09	9.216723e+09
2990	2991	Litecoin	LTC	2021-07-06 23:59:59	142.703568	135.924837	137.951668	138.985636	1.504907e+09	9.277627e+09

2991 rows × 10 columns

Fig 1.7: LTC Dataset

After cleaning the data, the dataset is visualised in a graphical form using the matplot library of python as shown in figure 3. The X-axis depicts the date of the recorded data and Y-axis depicts the Price on the particular date. The blue line in the graph represents the Open price, the red line represents the Closing price on the particular day, the Green line represents the High price on the particular day, the purple line represents the Low price on the particular day and the orange line represents the projection.

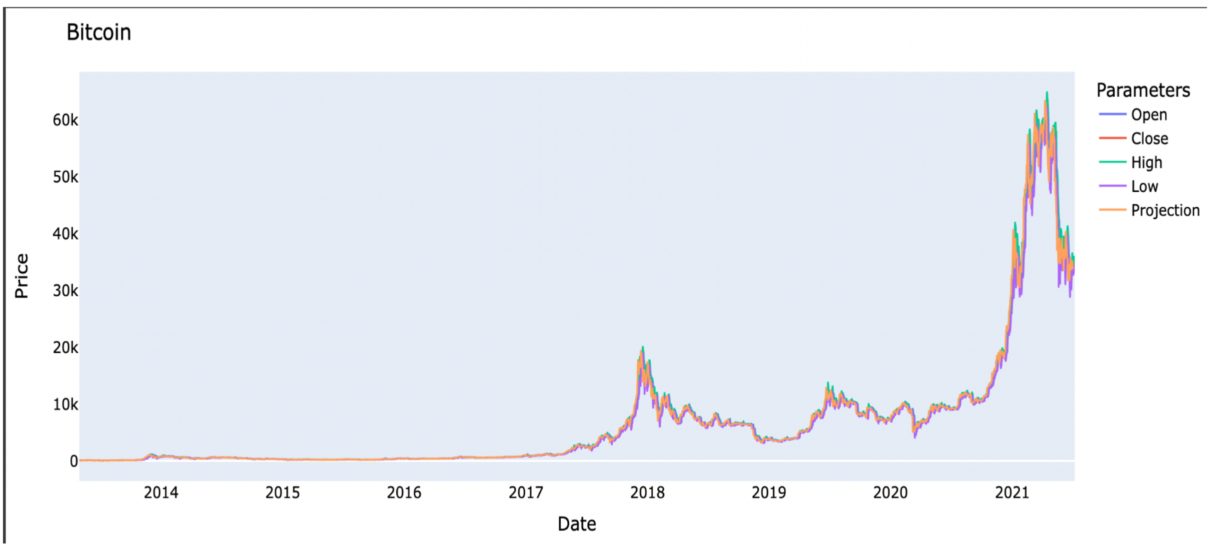


Figure 1.8: Visualisation of BTC

After visualising the date in graphical form, the dataset is split into training and testing datasets. The training data would be used for training of the model and the testing dataset would be used to test the model and check for its accuracy and other results.

C. After visualising the dataset in graphical form, Linear Regression model is applied on the dataset. Linear Regression analyses the data, analyses all the data points in the dataset and finds the best fit line for the data points, the mathematical equation for linear regression is

$$y = \alpha_1 x_1 + \alpha_2 x_2 + \ldots + \alpha_n x_n$$

Here α's are the linear coefficients and xs are the independent variables and y is the dependent variable. When plotted graphically, it gives a straight line fit after considering all the variables. Linear regression model is applied using sklearn library of python. The results are recorded for the linear regression model as shown in figure 4. The predictions based on the linear regression model are duly noted and recorded for comparison in the later stages

D. After Recording the results of the Linear Regression model, we train the Bayesian model using the same training dataset. Bayesian model is a statistical model where probability is used to represent the uncertainty within the model regarding the parameters of the model. Bayesian model is based on the Bayes theorem, according to which if the probability of an event which has already happened is given and another event is to happen is correlated with the event which has already occurred, then the probability can be calculated according to the mathematical formula:-

$$P(A|B) = P(B|A)P(A)P(B) \tag{3}$$

Here Bayesian model is applied using sklearn.linear model library in python. After applying the model, its accuracy is calculated and recorded for comparative analysis in a later stage as shown in figure 5.

E. After applying both the models the accuracy and results are compared of both the models and the best and optimal model is chosen.

F. After training and testing machine learning models we apply Deep learning models that are OLS, LSTM, RNN, ANN to get the comparative analysis of how these models are working on different datasets and how these models are performing in comparison to the machine learning models.

Chapter 2 Literature Survey

The research done in [1] has analysed the time series of the Bitcoin pro- cess by the use of Bayesian Neural Networks(BNN) which describes volatility in a time series format. To improve the variability which the author has sug- gested the use of different ML algorithms. Because of its special characteristics as a hybrid of cryptographic technology and a monetary unit, Bitcoin has recently attracted a lot of interest from researchers in the departments of economics, cryptography, and computer science. By examining the time series of Bitcoin processes, this paper illustrates the efficacy of Bayesian neural networks (BNN). Additionally, we choose the blockchain data's most pertinent features—those that have a significant impact on Bitcoin supply and demand and use them to build models that will enhance the accuracy of predictions made by current methods for determining the price of bitcoin. When modelling and making predictions about the Bitcoin process, they perform empirical investigations contrasting Bayesian neural networks with other linear and nonlinear benchmark models. Their empirical studies demonstrate that BNNs are effective at forecasting Bitcoin price time series and provide an explanation for the recent high volatility of Bitcoin prices.

Explore deep learning algorithms for cryptocurrency pricing. Previous work on deep learning for time series data has focused on recurrent neural networks. Consider the recently developed model 'R2N2', which contains residuals from vector autoregression of the RNN feature set. We have improved the computational efficiency of this algorithm to increase the accuracy of predicting returns for baskets of cryptocurrencies and show arbitrage opportunities in the market.

The research done in [2] has used the R2N2 model which includes residuals from vector autoregression in the RNN feature set. They have considered arbitrage opportunities in the market by taking a basket of crypto currencies. Time series models represent the primary set of statistical prediction methods for describing time dependencies in feature data. However, obtaining accurate time series forecasts is one of the most important problems in modern data mining, as these models often perform very poorly . To make matters worse, market prices update to reflect all available information, making it particularly difficult to predict time series for financial assets. Explore deep learning algorithms for cryptocurrency pricing. Consider the recently developed model 'R2N2', which contains residuals from vector autoregression of the RNN feature set. They have increased the computational efficiency of their system to better anticipate profits for cryptocurrency baskets and highlight market arbitrage possibilities.

According to one of the fundamental laws of asset valuation, the principle of no arbitrage, time dependence must be priced by the market . This barrier to predictability may explain why the application of neural networks to time series data dates back to his early 1990s . It has long been confined to areas such as agricultural sciences and climatology. These areas do not limit the predictability of data by arbitrage traders. Langkvist et al. and Heaton et al.Recently, we reviewed the literature on neural network prediction in the Ting series, citing the success of long-short-term memory networks in this area . A recently developed residual recurrent neural network algorithm called 'R2N2' first uses vector autoregression (VAR) to model the time series and then uses the resulting residuals as features in the recurrent neural network. use. The idea is that since VAR extracts the linearity of the autocorrelation, neural network optimization does not need to extract the linearity and can focus on learning the volatility structure. Although this type of hybrid model dates back to at least 2003, the majority of these applications are in non-financial sectors 19]. Adapt the R2N2 algorithm to the financial environment using VARMAX modelling. This allows reliance on a higher dimensional feature set by providing a dimensionality reduction of the optimization goal. We perform an architecture and hyperparameter search to build a predictive return LSTM network containing the residuals from this regression in the feature set. Evaluate the recall, precision, and distribution convergence of this model. Our results demonstrate the effectiveness of his R2N2 model for cryptocurrency pricing and demonstrate the existence of excess returns in cryptocurrency markets.

The work done by researchers in [3] predicts high frequency exchange rate of crypto currencies using a Deep Learn- ing model. They have focused on predicting the one minute exchange rates of Bitcoin-Ethereum currency. Most of the researchers have used either a single model or a hybrid model to predict the rates of the crypto currencies, in the proposed work of this paper, we have applied two machine learning models over a different set of crypto currency datasets. The main aim of the proposed model in this paper is to comparatively analyse the working of the models in different datasets of different crypto currencies. The researchers in [4] have focused on the emerging phenomenon of cryptocurrencies. The researchers have discussed the trends in the academic research related to cryptocurrencies and have tried to highlight the contributed work to the literature. The researchers in [5] have proposed a new clustering based methodology that provides additional views of financial behaviour of crypto currencies. The researchers have applied three different partial clustering algorithms to analyse the trend.

The algorithm designed in [6] to provide investment insights that reduce investor risk. It builds on previous work predicting binary price changes across 100 currencies through analysis of historical behaviour, tweet data, and news data. Overall, the quality of predictions was variable and difficult to assess. The model performed better than expected, achieving a very short time domain of 90 degree accuracy. However, this high accuracy can be strongly attributed to training data that is highly skewed in one direction. His algorithm is an LSTM-RNN that predicts price movements for the 100 most traded currencies. His input is saved every minute and includes:

1. Historical currency movements

2. Aggregate Twitter Sentiment by Currency / 3. Aggregate News Sentiment by Currency

First, they perform a series of data processing and cleansing techniques. They then run the data through a deep RNN containing multiple LSTM cells. Finally, a softmax layer is applied that returns a binary prediction of whether the currency price will rise or fall.Recently, a study by Pagolu et al. showed that autoregressive-recurrent neural networks outperform LSTMs on temporal prediction tasks. We achieved 59.00 curacy just by analysing past behaviour.

The work done in [7] predicts cryptocurrency prices considering social media and news. The number of linked news stories and social media posts is growing along with the economic and social ramifications of cryptocurrencies. Similar to conventional financial markets, a relationship between public opinion and cryptocurrency pricing seems to exist. In order to forecast Bitcoin price changes over a 24-hour period beginning at this hour in the future, the project analyses news and social media data and uses the strength of recurrent neural networks. Rather than tagging news and social media text with perceived sentiment, we tag the data for actual price changes over a specified period of time in the future, allowing models to predict price volatility directly. did. The model consisted of an embedding layer using a custom Word2Vec model, a single bidirectional LSTM layer, and a final linear activation layer for predicting price changes. The overall prediction accuracy was the highest (54.5%) using a model trained on Reddit posts from relevant cryptocurrency communities in predicting price movements 12 hours ahead. All models were implemented in Keras with Tensorflow as the backend.

In order to make binary predictions about the direction of future price movements of the three coins, nine binary classification models (one for each of the three data sources) were first built.. Bitcoin, Ethereum, Litecoin. However, the final implementation included three regression models, one for each data source, to predict the actual future price change of Bitcoin. This project helped answer two questions: First, can sentiment analysis on news headlines, tweets and Reddit posts accurately predict future Bitcoin price changes after 1, 2, 6, 12 and 24 hours.

Second, what's a better indicator of future bitcoin price if it can be predicted from an arbitrary dataset? Inputs to the system are headlines, tweets and text phrases from Reddit posts, kept in order. Occurrences to preserve the time-series nature of the data. Then a regression task is performed. A custom Word2Vec embedding layer is followed by a recurrent neural network (RNN) Numerical predictions of future bitcoin price change rates based on each text individually. All costs are then aggregated by hour and the average forecast is used to make the final forecast. This specified time value. While this system may be able to predict price changes directly, it is better at detecting whether certain headlines or media posts contain text historically shown to be associated with price changes. It may help.

The work done in [7] makes a model for prediction of cryptocurrency prices using limit order books as input. High-frequency trading, or algorithmic trading, is becoming more and more important on stock exchanges. In today's market, a significant portion of the daily trading volume is done by specialised firms using these techniques. In sophisticated stock markets, margins and arbitrage can be closed in an instant, making it almost impossible for anyone with very fast access to data without heavy machinery to gain an edge. The rise of cryptocurrency markets and cryptocurrency exchanges could reveal long-lost opportunities in the smaller algorithmic stock markets.

This project researches and develops deep machine learning models to predict future prices of digital assets like Bitcoin. We have developed a Recurrent Neural Network (RNN) that predicts future price movements of tradable and highly volatile digital assets like Bitcoin. The input to the model will be the limit order book data along with other historical indicators of supply and demand to create predictors. We have chosen digital assets for this project, but the principles and methods we have developed are transferable to any asset tradeable on an exchange.

This project clearly shows the correlation between the limit order book and future prices. Starting with fully connected binary classification models, we built various models ranging from RNNs to multi-class categorical classification and tested their performance on the development set. Achieving more than 70 curacies on the dev set was difficult and only came close, but the model we built on categorical taxonomy consistently outperforms Bitcoin even under the zero transaction cost model. Further work is to consider transaction costs and find a viable model.

The work done in [8] also uses RNN for prediction of cryptocurrency prices. Recurrent neural networks (RNNs) are a competitive forecasting technique in particular. I demonstrated how to triumph in the last M4 contest. However, well-known statistical models like ETS and ARIMA are not only well-liked because of their high accuracy, robustness, efficiency, and automaticity, but also because they are appropriate for lay people. The RNN operates here. There is still much to be done. In-depth empirical research and open source software frameworks are presented. His RNN design is currently in use for prediction. For instance, they get to the conclusion that RNNs can directly represent seasonality in series. The seasonal pattern in the sample is uniform. Deseasonalization is advised in all other cases. Automatically implemented comparisons with ETS and ARIMA Although RNN models are not a cure-all, they are often a viable option. In the past, professionals in distortion dominated the area of prognostication.

While arguing that neural networks (NNs) lack competition, NN enthusiasts have developed several sophisticated and original NN designs. There is typically no compelling empirical analysis compared to the more straightforward one. single-variate statistical approach. Many time series projections, in particular, backed this idea. M3, NN3, and NN5 tournaments, for example.

NNs were hence labelled as being inappropriate for prediction. The individual time series itself are typically too short to be simulated using complicated techniques, which is one of several potential causes for the historical underperformance of NNs. It's also possible that the time series' characteristics have evolved over time. For complex models, long time series might not have enough pertinent information. so use a sophisticated strategy to model sequencing. The right length is crucially derived from a system that is largely stable. Additionally, NN continues to draw flak for being a black box. As a result, forecasting specialists have usually utilised a more straightforward statistical approach. But the era of big data is now upon us. Businesses are gathering a vast amount of data. a year that contains crucial data on commercial trends. Contextualising big data More data than that is not always there in individual time series. In such a setting, this often signifies that there are several connected time series from the same domain. Techniques for univariate forecasting that focus just on a single time series often fall short of making accurate forecasts. They are not appropriate for big data environments where one model may simultaneously learn from several comparable time series. However, more sophisticated models, such as NNs, gain the most from the accessibility of vast amounts of data.

As a result, a number of machine learning and statistical approaches, including many others, are being replaced by NNs, according to study. Most notably, our recurrent neural network (RNN) displayed outstanding performance and was successful in taking first place in the most recent M4 competition. The Multi-Quantile Recurrent Neural Network (MQRNN), Spline Quantile Function RNN, and deep state space models for probabilistic prediction are additional examples of recent innovations in this field that have been successful. The literature, according to Makridakis et al., is filled with prediction methods for machine learning and neural networks. They emphasise that these approaches are typically not carefully assessed against statistical standards and are typically pointed out as performing worse than these. He may have played a major role in the planning of the M4 competition. Furthermore, implementations of the datasets or code used for NN-related predictive studies are frequently not made available to the general public and have problems with claimed performance being able to be replicated. The prediction community is now in a tough condition due to the absence of available code implementations.

to modify such research to effective prognostic objectives. Contrarily, well-known statistical models like ETS and ARIMA, which historically assist prediction in univariate situations, have not grown in popularity just because of their excellent accuracy. Additionally, it has the benefit of being comparatively easy to use and is sturdy, efficient, and automated. A number of forecasting-related features, such as seasonal and trend decomposition (STL decomposition) using ARIMA, ETS, and Loess, are offered by the forecasting package in the R programming language, for instance. incorporates statistical techniques into a single, well-rounded software programme. As a result of its simplicity, accuracy, robustness, and usability, this programme performs better than many others that were developed subsequently.

The first step in developing this system would be to gather relevant data from various sources, such as cryptocurrency exchanges, social media platforms, news websites, and financial analysis reports. This data would include information about historical cryptocurrency prices, trading volumes, market capitalization, and other relevant indicators.

Once the data is collected, it would need to be preprocessed and cleaned to remove any irrelevant or inconsistent information. This step is crucial to ensure the accuracy of the deep learning models that will be trained on the data.

Next, a deep learning model would be developed to analyze the cryptocurrency data and identify trends and patterns. The model would be trained using supervised learning techniques, with historical data used as input and future price movements used as output. The model would be fine-tuned and optimised to achieve the highest possible accuracy.

After the deep learning model has been developed and trained, it would be integrated into a recommendation system that provides buy, hold, or sell signals for various cryptocurrencies based on the trends and patterns identified by the model. The recommendation system would also take into account various other factors, such as market conditions, news events, and investor sentiment, to provide more accurate and personalised recommendations.

Finally, the system would be deployed and made available to users through a web-based interface. Users would be able to view real-time cryptocurrency prices, receive personalised recommendations based on their investment goals and risk tolerance, and track their portfolio performance over time. The system would also provide tools for backtesting investment strategies and analysing the performance of different cryptocurrencies over time.

Overall, this system development would require a team of experienced data scientists and software developers, as well as access to high-quality data sources and computing resources. However, if developed successfully, it could provide investors with valuable insights and recommendations for navigating the complex and rapidly changing world of cryptocurrency investing.

Chapter 3 System Development

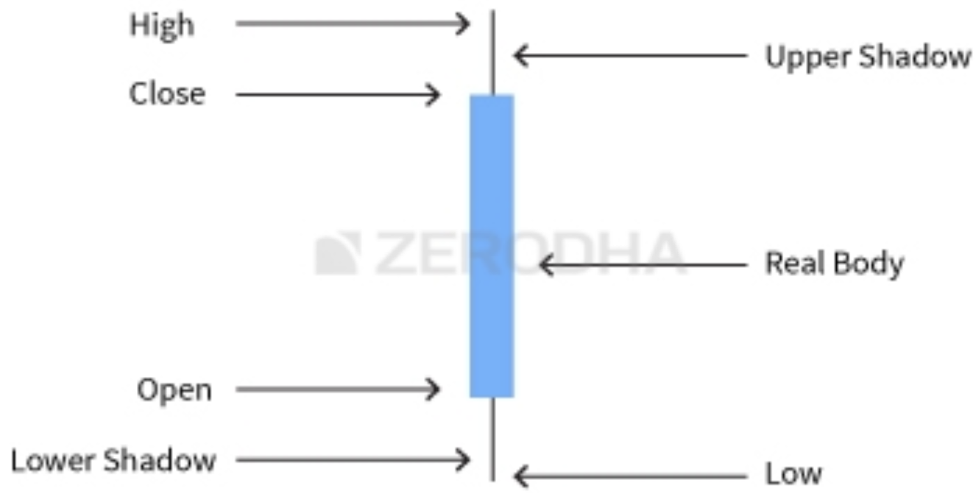
3.1 Technical Analysis

The preliminary technique used to analyse crypto currency or any asset to be traded per say is technical analysis. The original technique performed by many traders is technical analysis. In technical analysis techniques, the trader analyses the charts of the historical data of the cryptocurrency using various technical analysis techniques.

The historical time series data of the crypto currency consists of the Open, Low, High and Close of the cryptocurrency every day for a particular amount of time. The ‘Open’ is the opening price of any cryptocurrency for any particular day. This means the price at which the cryptocurrency started to trade on that particular day, or the price of the particular cryptocurrency at which it started trading on that day or the price at which the first trade of the day was performed on the particular cryptocurrency. The ‘Close’ means the closing price of any cryptocurrency for any particular day. This means the price at which the cryptocurrency ended for trading on that particular day, or the price of the particular cryptocurrency at which it ended trading on that day or the price at which the last trade of the day was performed on the particular cryptocurrency. The ‘Low’ means the lowest price of any cryptocurrency for any particular day. This means the price at which the cryptocurrency was at the lowest to trade on that particular day, or the least price of the particular cryptocurrency at which it was trading on that day or the lowest price at which any trade during the day was performed on the particular cryptocurrency.

All of this data is converted into candlestick charts and thus used for analysing the cryptocurrency. A candlestick charting technique is an old Japanese charting technique used by the rice traders of Japan in the 18th century. In candlestick charts, in the candlestick charting method, the prices of the cryptocurrency are arranged in the way as shown in figure 4. The higher wick represents the cryptocurrency high on that specific day, and the lower wick represents its low on that specific day. The candlestick's main body endings stand in for the concepts of open and close.

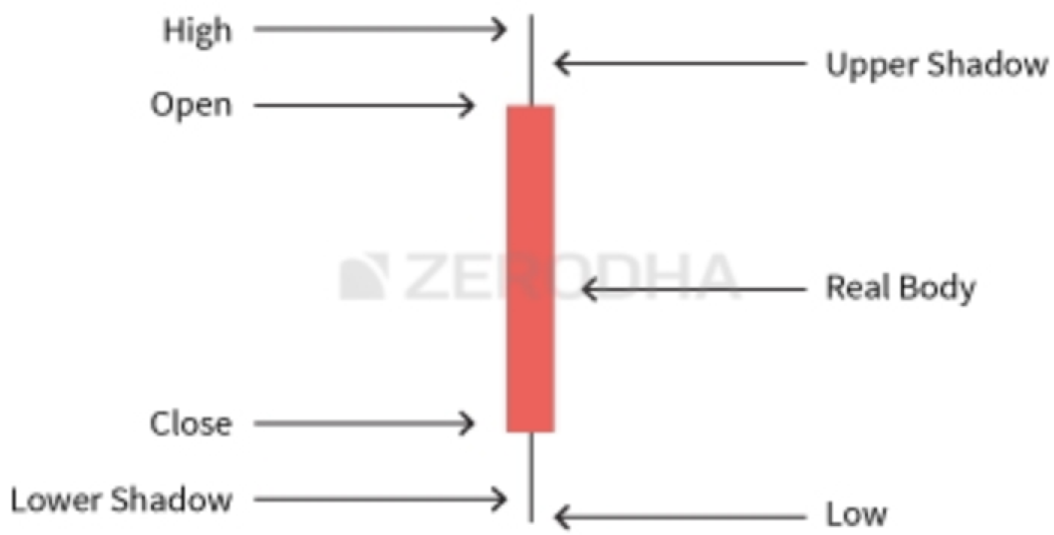
A blue/green candle represents a positive day, i.e. when the closing price of the cryptocurrency is higher than the opening price of the cryptocurrency on the particular day as shown in the figure 2.1.



Source: Zerodha.com

Figure 3.1: Blue Candlestick

Similarly, a red/black candle represents a negative day, i.e. when, as seen in figure 5, the cryptocurrency's closing price on a given day is lower than its initial price.



Source: Zerodha.com

Figure 3.2: Red Candlestick

Now the historical time series data of the cryptocurrency is charted using the candlestick chart as discussed above. The charts are then analysed by traders to predict the possible trend of the cryptocurrency as shown in figure 6. All the candlesticks are arranged in the time series so as to create a chart of all the candlesticks in a particular time period.

Figure 3.3: Candlestick Chart

The trader can easily analyse these charts which contain almost all the information about the prices of the cryptocurrency in a concise way. It contains all the pricing information of the cryptocurrency in a single chart. The pricing information can be used to predict the future price of the cryptocurrency.

The chart can suggest the trend or the direction of the price in which it can possibly move. If the relative price is higher than the previous prices of the particular cryptocurrency then the direction of that particular cryptocurrency is said to be going upwards or the trend is said to be positive/higher. If the relative price is lower than the previous prices of the particular cryptocurrency then the direction of that particular cryptocurrency is said to be going downwards or the trend is said to be negative/downward.

Candlesticks are of mainly of two types-

i) Single Candlesticks are those candlestick patterns which consist of a single candlestick and the analysis is performed on the basis of that candlestick alone.Single candlestick patterns mainly consist of ‘Marobuzo’, ‘Spinning Tops’, ‘Dojis’ and ‘hammer’. All these are different types of candlestick patterns.

ii) Multiple Candlesticks are those candlestick patterns which consist of multiple candlesticks and the analysis of the cryptocurrency is performed on the basis of those candlesticks as a whole. The main patterns in multiple candlestick patterns are ‘Engulfing Pattern’, ‘Piercing Pattern’, ‘Dark Cloud Cover’, ‘Harami’, ‘Morning Star’, ‘Evening Star’, ‘Shooting Star’. All of these are multiple candlestick patterns which can be used to analyse a particular cryptocurrency.

Another technique in technical analysis is ‘Support and Resistance’ often abbreviated as ‘S&R’. In this technique, in the candlestick chart of the particular cryptocurrency, a zone of price action, such that it acts either as a support or as a resistance to the price from going down or going up respectively. The support and resistance is a zone that is formed mainly due to sentiment analysis of the investors and traders. When traders and investors believe that a particular price is high, they start selling the particular cryptocurrency and that creates a resistance. When traders and investors believe that the price of a cryptocurrency is too low, they start buying the cryptocurrency and it thus increases the price of that cryptocurrency from that price zone, thus creating a support. This is shown in the figure 7 below. In the figure, the upper price action zone represents the resistance zone and the lower price action zone represents the support zone.

Figure 3.4: Support and Resistance

This phenomenon is basically due to the fact that high demand creates lesser supply availability and thus the prices increase, and when the people are less interested in buying and more bent towards selling, it creates a high supply and less demand, as there are less people to buy, thus creating a negative effect on the price of the cryptocurrency and reducing its price.

Technical Analysis also consists of analysing volumes. Volumes helps a technical analyst to check whether a move in a cryptocurrency is valid or not, because if the trend of the cryptocurrency is supported with increasing volume, this means that the trend is supported by the majority of the investors and the trend is a valid trend. If the volume of the cryptocurrency is decreasing and the prices are going in a particular direction, no matter if they are moving up or moving down, the trend is not supported by the majority of the traders and investors and thus the trend is perishable and can be vanished anytime even with a slightest change in the market sentiment.

Fibonacci retracements are one more technique used in technical analysis to identify the retracement levels of price action zones. This technique is also widely used by traders.

A line that crosses the whole stock chart will nearly always be visible while viewing a stock chart on a trader's trading terminal. Technical indicators are the names given to these lines. Traders can examine a security's price fluctuations with the use of technical indicators.

Successful traders invented separate trading techniques called indicators and spread them around the world. Traders can use indicators as a supplement to technical studies (candlesticks, volume, S&R) to help them make trading decisions because they are based on pre-configured logic. For buying and selling, trend confirmation, and occasionally trend prediction, indicators are helpful.

Leading and trailing indicators are the two different categories. Leading indicators direct price movement. In other words, it typically announces a change in trend or its occurrence in advance. Although this seems intriguing, it's crucial to remember that not all leading signs are reliable. Leading indicators have a history of sending misleading indications. As a result, traders should use leading indicators with extreme caution. In actuality, as a trader gains expertise, employing leading indicators becomes more effective.

The majority of leading indicators are known as oscillators because of their propensity to oscillate over a small range. Usually, this oscillates like an oscillator between two extreme values. as an example, 0 to 100. Depending on the oscillator value, trades are assessed differently (55, 70, etc.).

On the other hand, a trailing indicator follows the price. In other words, it typically denotes that a trend has changed or reversed after it has already started. We could be questioning why we should receive a notification after an event has already happened. Better late than never, I suppose. Among lagging indicators, the moving average is one of the most often used.

Moreover there are many technical indicators that are also used to identify the trend of the cryptocurrency. Indicators like moving averages, abbreviated as MA, relative strength indicator(RSI), moving average convergence divergence(MACD), are widely used by traders for help in executing and planning their trades. These indicators give a view upon how the cryptocurrency can move in the coming time. Trend indicators are very widely used by many traders in the trading world, these help particularly in identifying the trend of the particular cryptocurrency.

RSI, often known as the Relative Strength Index, is a popular indicator created by J. Welles Wilder. A crucial momentum indicator that aids in spotting trend reversals is the RSI. Expectations are made for the market based on the latest indicator value and the RSI indicator's range of 0 to 100.

The term Relative Strength Index is misleading as it indicates the intrinsic strength of a security rather than comparing the relative strength of two securities. The most widely used leading indicator, the RSI, provides the clearest signals when the market is sideways or not trending. Thus technical analysis is a very handy tool when it comes to trading, but it is a bit hefty to learn and to execute.

3.2 Model Development

The first step in developing this system would be to gather relevant data from various sources, such as cryptocurrency exchanges, social media platforms, news websites, and financial analysis reports. This data would include information about historical cryptocurrency prices, trading volumes, market capitalization, and other relevant indicators.

Once the data is collected, it would need to be preprocessed and cleaned to remove any irrelevant or inconsistent information. This step is crucial to ensure the accuracy of the deep learning models that will be trained on the data.

Next, a deep learning model would be developed to analyse the cryptocurrency data and identify trends and patterns. The model would be trained using supervised learning techniques, with historical data used as input and future price movements used as output. The model would be fine-tuned and optimised to achieve the highest possible accuracy.

3.3 Deep learning models

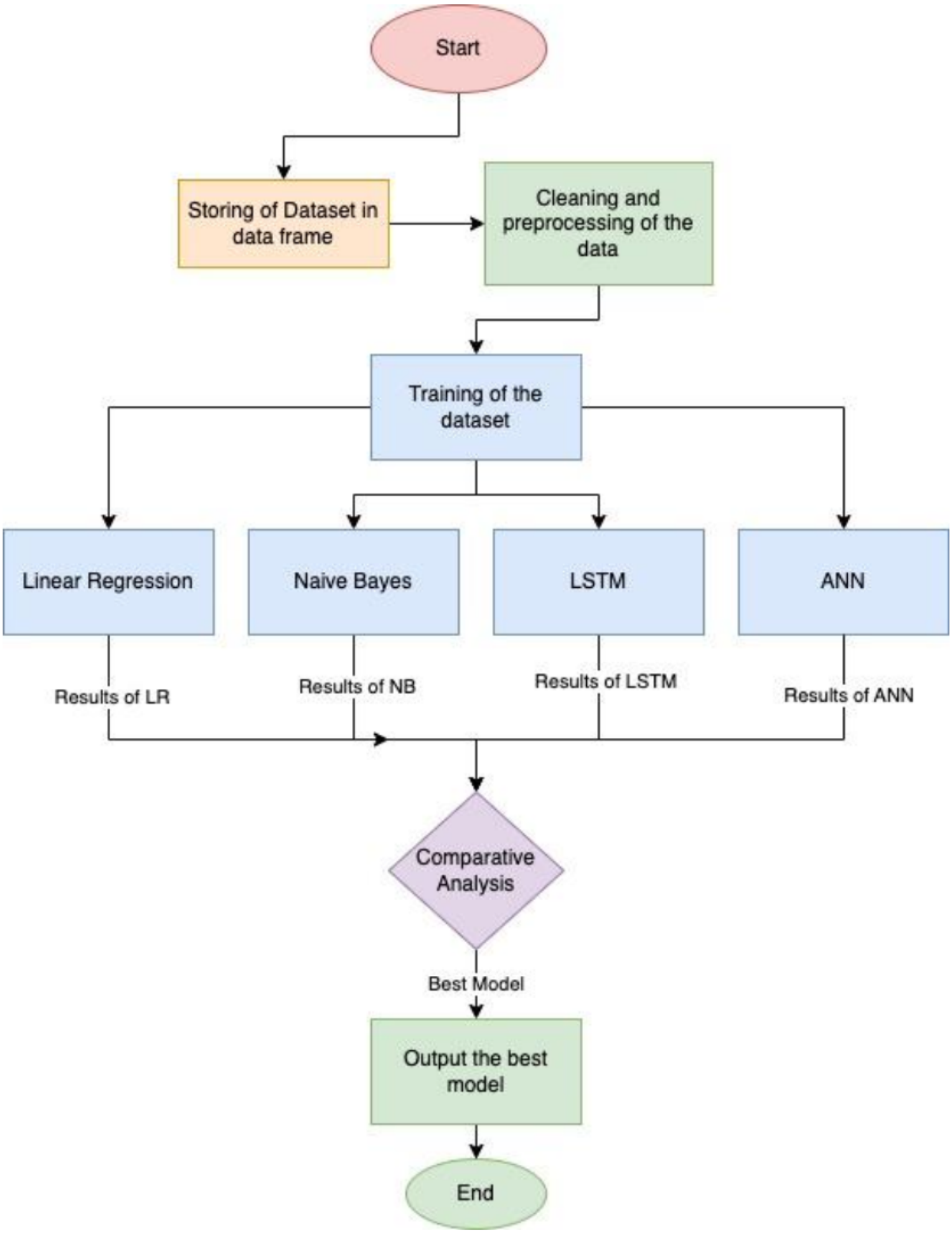


Fig 3.5 Deep learning flowchart

3.4.1 Long short-term memory network(LSTM)

An example of a specific type of recurrent neural network is the long short-term memory network (LSTM) (RNN).

LSTM operation: Three gate components make up the distinctive network structure known as LSTM. The input gate, forgetting gate, and output gate are the three gates that make up an LSTM unit. When information enters the LSTM network, it may be selected by rules. The forgetting gate will remove data that doesn't follow the algorithm, leaving just the data that does. The experimental data in this study are actual historical data that were obtained from the Internet. Three data sets were used in the studies. There is a need for an optimization method with faster convergence and less resource use. employing an LSTM neural network with a built-in LSTM layer and an automatic encoder. LSTM is used in place of to stop gradients from exploding and fading.

LSTM Architecture

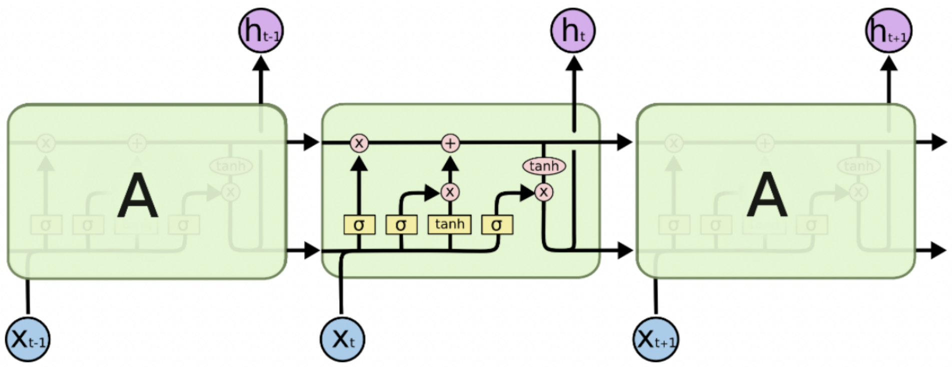


Fig. 3.6: LSTM Architecture

Forget Gate:

Data from the cell state is deleted via a forget gate.

By multiplying a filter, the information that is less important or no longer necessary for the LSTM to grasp anything is eliminated.

This is necessary to improve the LSTM network's performance.

h_{t-1} and X_{t-1} are the gate's two inputs. h_{t-1} denotes the hidden state or output from the cell before, whereas x t denotes the input at that specific time step.

Input Gate:

1. Choosing which values should be added to the cell state by the application of a sigmoid function. This is similar to the forget gate in that it only serves as a filter for all the data from h_{t-1} and x_t.

2. Constructing a vector with each value that might be added to the cell state (as determined by h_{t-1} and x_t). This is accomplished using the tanh function, which produces values between -1 and +1.
3. After dividing the value of the produced vector by the regulatory filter's (the sigmoid gate's) value, adding this helpful information to the cell state (the tanh function).

Output Gate:

Once more, there are three phases that make up an output gate's functioning.

Before constructing a vector, scaling the values to the range of -1 to +1 by applying the tanh function to the cell state.

The values that must be produced from the vector created above are controlled by a filter made up of the values h_{t-1} and x_t. Once more using a sigmoid function, this filter.

The vector produced in step 1 is multiplied by the value of this regulatory filter, and the result is sent as an output as well as to the hidden state of the subsequent cell.

3.3.2 Recurrent Neural Network (RNN)

Recurrent Neural Networks (RNNs) are a class of neural networks that are designed to handle sequential data, such as time series or natural language. Unlike traditional feedforward neural networks, RNNs have loops that allow information to persist over time. This enables them to capture temporal dependencies in the data, making them well-suited for applications like speech recognition, machine translation, and music generation.

At the heart of an RNN is a hidden state vector, which is updated at each time step based on the current input and the previous hidden state. The updated hidden state is then used to make a prediction or generate an output. This process is repeated for each time step, allowing the network to build a memory of past inputs and generate context-dependent predictions.

One of the most popular variants of RNNs is the Long Short-Term Memory (LSTM) network, which uses memory cells and gating mechanisms to selectively update and forget information. This helps to overcome the vanishing gradient problem that can occur in traditional RNNs, where the gradient signal can become too small to update the network parameters effectively.

In the context of cryptocurrency trend analysis, RNNs can be used to model and predict the behaviour of cryptocurrency prices over time. By training an RNN on historical price data, the network can learn patterns and relationships that can be used to make future predictions. For example, an RNN could be used to predict whether the price of Bitcoin is likely to rise or fall in the next hour, based on historical price data and other relevant factors such as trading volume and news sentiment.

RNNs can also be used to detect anomalies in cryptocurrency price data, such as sudden price spikes or drops. By training an RNN to model the normal behaviour of cryptocurrency prices, any deviations from this behaviour can be flagged as potential anomalies. This can help traders and analysts to identify potentially profitable opportunities or avoid risky investments.

Overall, RNNs are a powerful tool for analysing time series data, and their ability to capture temporal dependencies makes them well-suited for applications in finance and cryptocurrency analysis.

3.3.3 Artificial Neural Network (ANN)

Artificial neural networks (ANNs) are a type of machine learning algorithm that are modelled after the structure and function of the human brain. ANNs are composed of multiple layers of interconnected nodes, or neurons, that process and transmit information to other neurons in the network. Each neuron receives input from other neurons and computes a weighted sum of that input, which is then passed through an activation function to produce an output. ANNs are trained using a process called backpropagation, where the network's output is compared to the desired output and the weights of the neurons are adjusted accordingly to minimise the error.

ANNs have been applied to a wide range of problems, including image and speech recognition, natural language processing, and financial forecasting. In the context of financial forecasting, ANNs can be used to analyse complex patterns in financial data and make predictions about future trends. For example, ANNs can be used to predict stock prices, identify market trends, and forecast economic indicators such as GDP and inflation.

Cryptocurrency trend analysis involves using statistical methods to analyse historical price data and make predictions about future trends in the cryptocurrency market. ANNs can be used to perform this analysis by analysing large amounts of historical price data and identifying patterns and trends that can be used to make predictions about future prices. ANNs are particularly useful in this context because they can identify complex patterns in the data that may not be apparent to human analysts.
To use ANNs for cryptocurrency trend analysis, the network must be trained using historical price data and other relevant financial data such as trading volume and market capitalization. Once the network is trained, it can be used to make predictions about future price trends based on current market conditions. However, it is important to note that ANNs are not infallible and their predictions may not always be accurate, particularly in highly volatile markets such as the cryptocurrency market.

ANNs are a powerful tool for analysing complex patterns in financial data and making predictions about future trends. When applied to cryptocurrency trend analysis, ANNs can be used to identify patterns and trends in historical price data and make predictions about future prices. However, it is important to exercise caution when using ANNs for financial forecasting and to consider other factors such as market sentiment and regulatory changes that may impact cryptocurrency prices.

3.4 Trend Analysis Using Tweets

The machine learning algorithm used in the datasets is not 100% efficient to get to know about the trend of cryptocurrencies. There are various factors affecting the fluctuations in real time. So we have tried to capture that attribute and tried to analyse the real time tweets related to cryptocurrencies.

Based on data provided by the user in the form of hashtags and usernames, the user's tweets from Twitter are collected. The classification of tweets began with the collection of tweets. It is possible to gather Twitter data using the Twitter API. Key input is used to perform authentication using the RAuth library. To perform the Handshake protocol, the Twitter application needs Consumer Key, Consumer Secret, Access Token, and Access TokenSecret.

Following that, a PIN is created for the programme to access tweets and a certificate is downloaded.

This approach deals with the issue of sentiment analysis on Twitter, which is the classification of tweets into those with positive, negative, or neutral emotion. Twitter is a social networking and microblogging website that enables users to post 140-character maximum status updates. More than 200 million people have signed up for the service, of which 100 million are active users and half of them log in daily, producing approximately 250 million tweets every day. We intend to represent the public opinion by analysing the sentiments stated in the tweets in light of this significant usage. Any trend study should include a sentiment analysis of the general populace. In order to give users a visual overview of what is happening in the outside world, we have tried to build a tkinter interface.

Phase I of the process involves gathering tweets by gathering input in the form of hashtags or usernames. Except for COVID HASHTAG SENTIMENT, where a readymade csv file is utilised since we are representing a larger dataset that has to be shown quickly, the tweets gathered are those that are streaming live online. Tweepy was used to do all of this. We had to authenticate the API before we could start gathering the tweets.

Twitter Authentication: To use the Twitter Streaming API, we need to obtain 4 pieces of information from Twitter. Access token, Access token secret, API key, and API secret When building an application on Twitter, these 4 elements are used for Twitter authentication. A developer's account is necessary. We kept our login information in a csv file, and we used the dataframe in FIG. below to get the necessary data.

```
csv_file = pd.read_csv('Twitter API Credentials.txt')
```

```
api_key = csv_file['info'][0]
api_secret = csv_file['info'][1]
access_token = csv_file['info'][2]
access_token_secret = csv_file['info'][3]
```

```
try:
    authenticate = tweepy.OAuthHandler(api_key, api_secret)
    authenticate.set_access_token(access_token, access_token_secret)
    api_obj = tweepy.API(authenticate, wait_on_rate_limit = True)
except:
    print("Error:AUTHENTICATION FAILED")
```

Fig. 3.7: Fetching Twitter Data

The cleaned tweets are processed in step II. When tweets are cleaned, extra text additions like URLs, numerals, and special characters are removed to make them smaller for comparison.

```
def cleanText(text):
    text = re.sub(r"@\w+\s","", text) #remove @
    text = re.sub(r"@[A-Za-z0-9]+", "", text)
    text = re.sub(r"#","",text) #Remove hastags
    text = re.sub(r"RT[\s]+", "", text)
    text = re.sub(r"https?:\/\/\w+\.\w+\.?\/?\w+","",text)
    text = re.sub(r":","",text)
    text = re.sub(r"_","",text)

    return text

tweet_df['Text'] = tweet_df['Text'].apply(cleanText)
```

Fig. 3.8: Cleaning Data

With the use of TextBlob, which is seen in Fig, the tweets are then categorised as positive or negative during phase III. Python's TextBlob package is used to process textual data. It offers a straightforward API for getting started with typical natural language processing (NLP) activities including part-of-speech tagging, noun phrase extraction, sentiment analysis, classification, translation, and others. After that, the GUI is used to display the final data.

3.4.1 Why we used Tweepy API for cryptocurrency Trend Analysis?

A. <u>**Twitter Sentiment Analysis**</u>

The tweet or comments' attitude might serve as helpful indications for a variety of applications. Positive and negative words can be used to classify sentiments into two categories. Sentiment analysis is a method of natural language processing used to measure an opinion or sentiment expressed in a group of tweets.

B. **Technique Used For Sentiment Analysis**

To analyse the tweeter data, we employed TextBlob. As it sits on the enormous shoulders of NLTK and Pattern, it is analytically effective. It also includes features like word frequency analysis, lemmatization, word inflection (pluralization and singularization), part-of-speech tagging, classification (Naive Bayes, Decision Tree), tokenization (dividing text into words and sentences), word and phrase frequencies, parsing, and n-grams. WordNet integration and adding other models or languages make it simple to determine the emotion of a given text.

3.4.2 Trend Analysis through tweets design

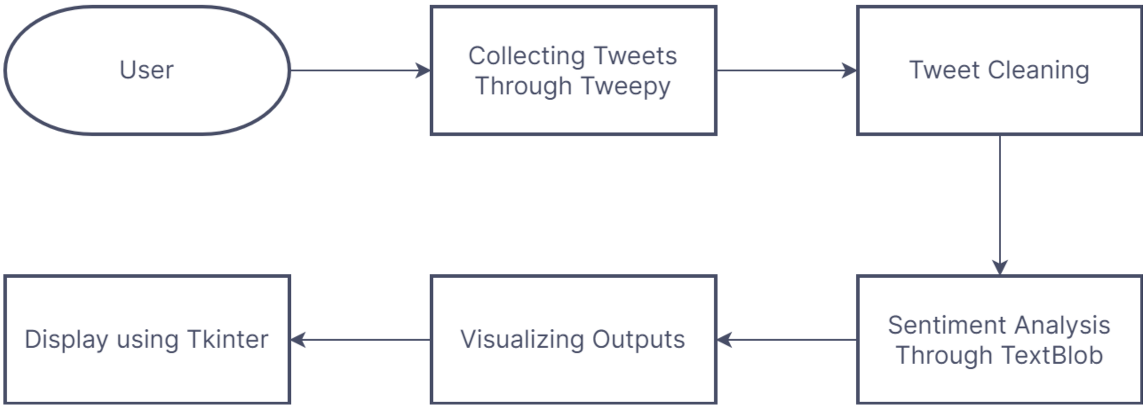


Fig. 3.9 Flowchart of Trend Analysis through Tweets

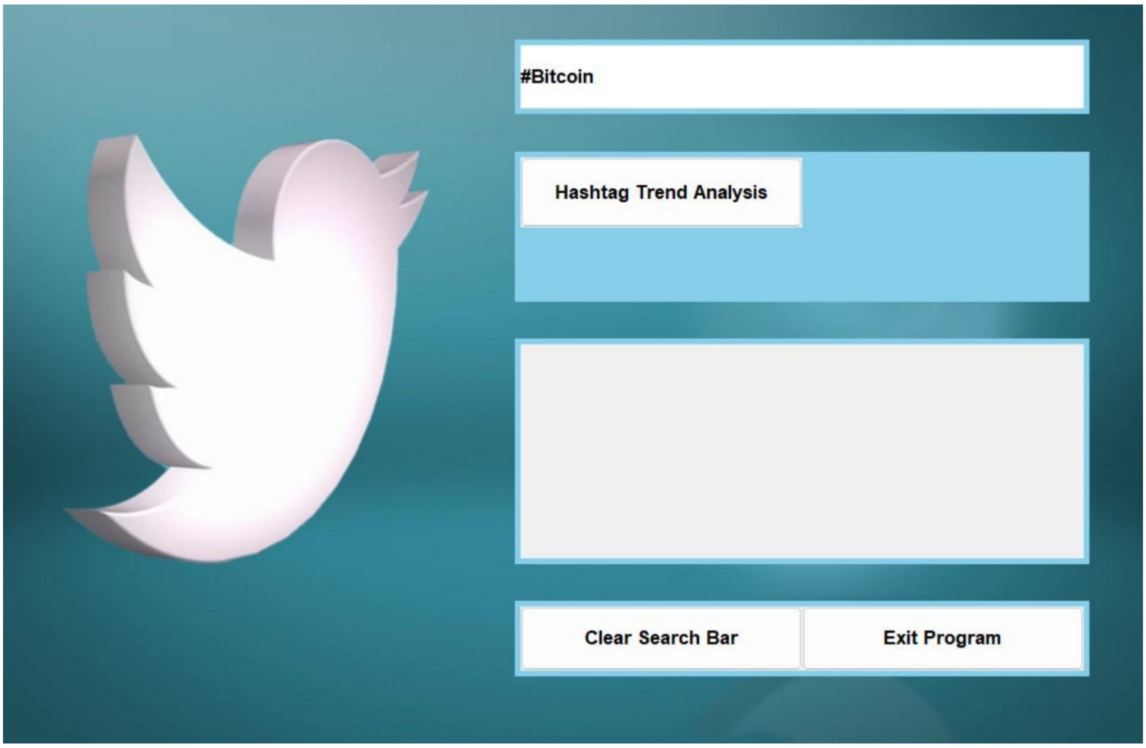


Fig. 3.10: Design of Trend Analysis through Tweets

Chapter 4 Performance Analysis

4.1 Performance Analysis Using Machine

Bitcoin

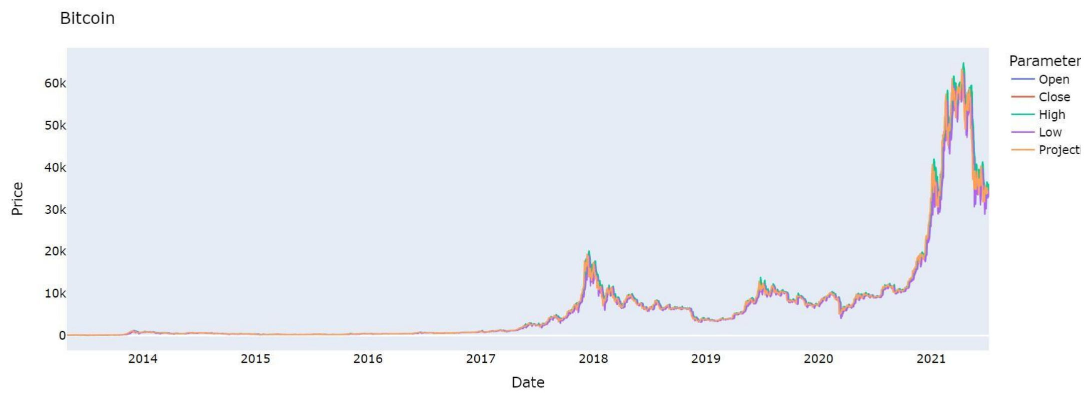


Fig. 4.1: BTC visualisation

```
print("Accuracy=>",(linReg.score(x_test_Bitcoin, y_test_Bitcoin)))
Accuracy=> 0.98132553617588 59
```

```
Linear Regression Confidence:  0.9813255361758859
98.1325536175886 %
```

```
r2 Score Of Test Set : 0.9813259666210432
```

```
print("Accuracy=>",(model_bayes.score(x_test_Bitcoin, y_test_Bitcoin)))
Accuracy=> 0.9813259666210432
```

Fig. 4.2: Results of BTC

Cardano

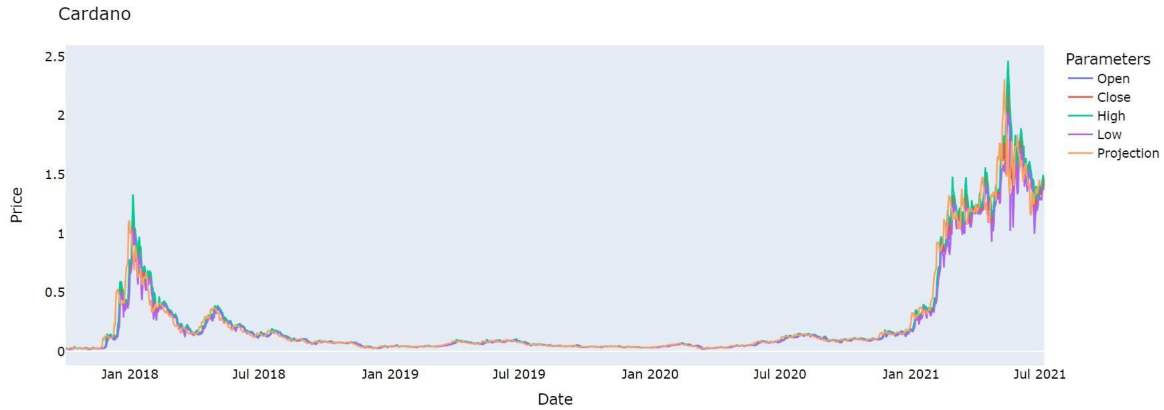


Fig. 4.3 Visualisation of ADA

```
print("Accuracy=>",(linReg.score(x_test_Cardano, y_test_Cardano)))
```

```
Accuracy=> 0.9681699095429076
```

```
Linear Regression Confidence:  0.9681699095429076
96.81699095429076 %
```

```
r2 Score Of Test Set : 0.9681690670733933
```

```
print("Accuracy=>",(model_bayes.score(x_test_Cardano, y_test_Cardano)))
```

```
Accuracy=> 0.9681690670733933
```

Fig. 4.4 Results of ADA

DogeCoin

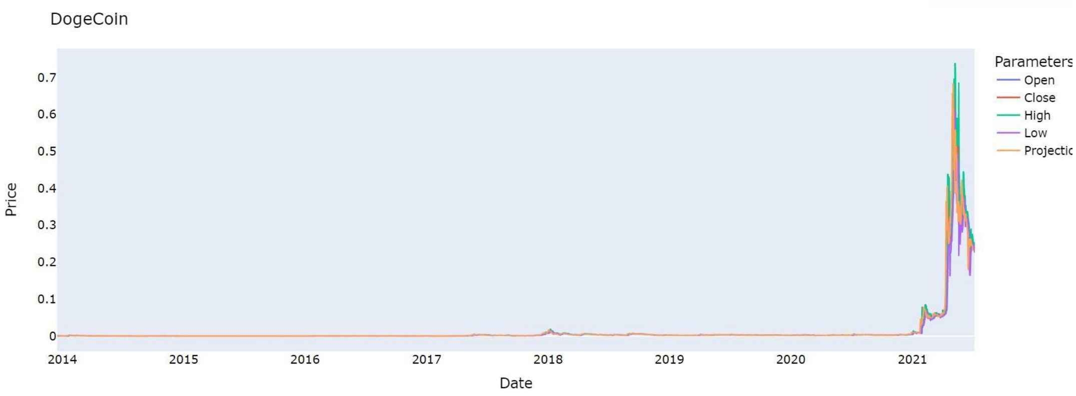


Fig. 4.5: Dogecoin Visualisation

```
[26] print("Accuracy=>",(linReg.score(x_test_DogeCoin, y_test_DogeCoin)))

Accuracy=> 0.9050085378168832
```

```
linReg_confidence = linReg.score(x_test_DogeCoin,y_test_DogeCoin)
print("Linear Regression Confidence: ",linReg_confidence)
print(linReg_confidence*100,'%')

Linear Regression Confidence:  0.9050085378168832
90.50085378168832 %
```

```
r2 Score Of Test Set : 0.9049980931597059
```

```
print("Accuracy=>",(model_bayes.score(x_test_DogeCoin, y_test_DogeCoin)))

Accuracy=> 0.9049980931597059
```

Fig. 4.6: DOGE Results

Ethereum

Fig. 4.7: Ethereum Visualisation

```
print("Accuracy=>",(linReg.score(x_test_Ethereum, y_test_Ethereum)))

Accuracy=> 0.9762221824094679
```

```
r2 Score Of Test Set : 0.9762218860226073
```

```
Linear Regression Confidence:  0.9762221824094679
97.6222182409468 %
```

```
print("Accuracy=>",(model_bayes.score(x_test_Ethereum, y_test_Ethereum)))

Accuracy=> 0.9762218860226073
```

Fig. 4.8 Results of ETH

LiteCoin

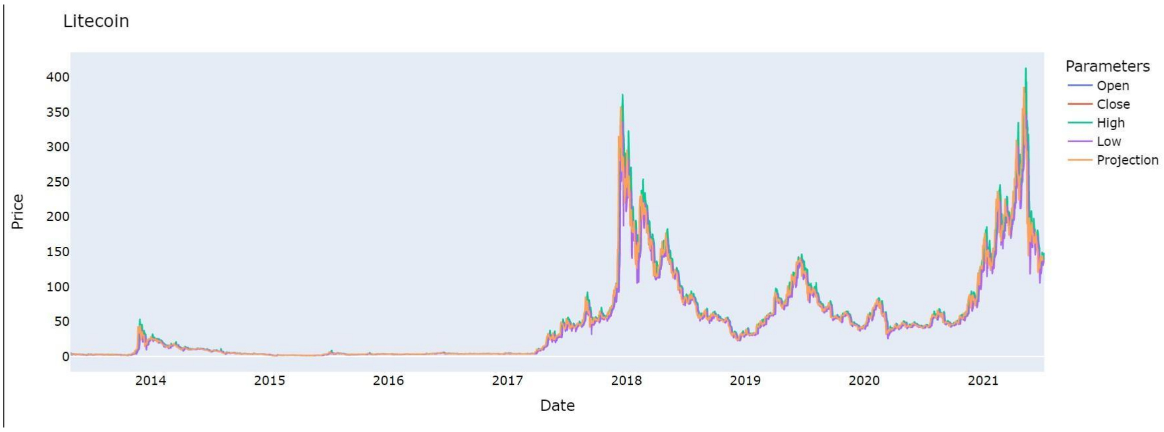


Fig. 4.9: LTC Visualisation

```
print("Accuracy=>",(linReg.score(x_test_Litecoin, y_test_Litecoin)))

Accuracy=> 0.9631930094035455
```

```
Linear Regression Confidence:  0.9631930094035455
96.31930094035455 %
```

```
r2 Score Of Test Set : 0.9631940295203821
```

```
print("Accuracy=>",(model_bayes.score(x_test_Litecoin, y_test_Litecoin)))

Accuracy=> 0.9631940295203821
```

Fig. 4.10: LTC Results

Solana

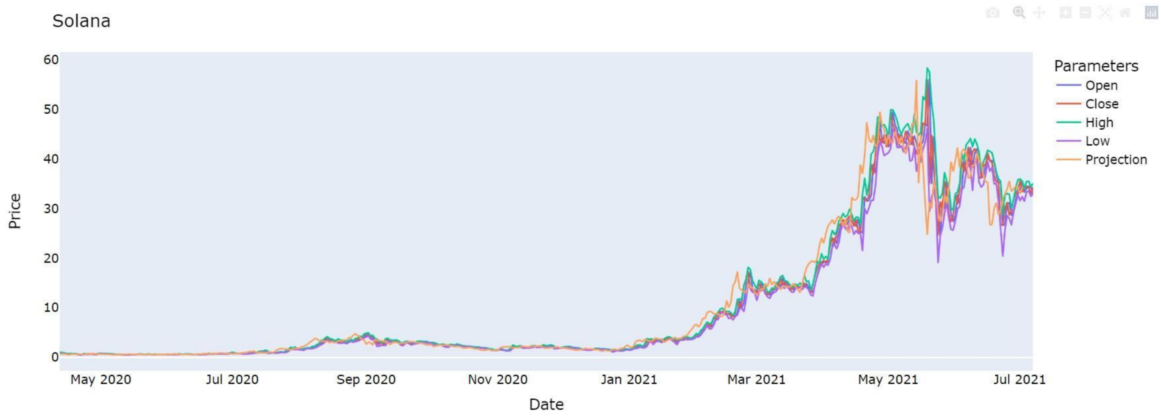


Fig. 4.11: Solana Visualisation

```
print("Accuracy=>",(linReg.score(x_test_Solana, y_test_Solana)))

Accuracy=> 0.9457087941311823
```

```
Linear Regression Confidence:  0.9457087941311823
94.57087941311822 %
```

```
r2 Score Of Test Set : 0.9457252983760602
```

```
print("Accuracy=>",(model_bayes.score(x_test_Solana, y_test_Solana)))

Accuracy=> 0.9457252983760602
```

Fig. 4.12: SOL Results

Comparative Analysis

Table 4.1. Comparative Analysis of Machine Learning Models

Model	Accuracy	R^2 Score
Linear Regression	0.984051	0.987038
Bayesian	0.986421	0.985766

4.2 Performance Analysis Using Deep Learning Models

LSTM

```
[ ]  actual_lstm = test_y
     predicted_lstm = test_predict[:, 0]
     evaluate_forecast_results(actual_lstm, predicted_lstm)

     R2 Score:  0.99
     MAE :  51.75
     MSE:  10140.24
     RMSE:  100.7
     NRMSE:  0.0905
     WMAPE:  0.0003
```

Fig 4.13 LSTM Results

RNN

```
[ ]  evaluate_forecast_results(actual_, predicted_)

     R2 Score:  0.99
     MAE :  52.11
     MSE:  10636.07
     RMSE:  103.13
     NRMSE:  0.0925
     WMAPE:  -0.0104
```

Fig 4.14 RNN Results

ANN

```
[ ]  evaluate_forecast_results(test_y, predicted_value)

     R2 Score:  0.99
     MAE :  61.1
     MSE:  13673.08
     RMSE:  116.93
     NRMSE:  0.1051
     WMAPE:  -0.0291
```

Fig 4.15 ANN Results

Comparative Analysis

Table 4.2. Comparative Analysis of Deep Learning Models (ETH Dataset)

Model	MAE	R^2 Score
ANN	51.75	0.982256
RNN	52.11	0.980233
LSTM	61.1	0.981380

4.3 Performance Analysis of trend analysis using tweets

Positive tweets displaying using word cloud

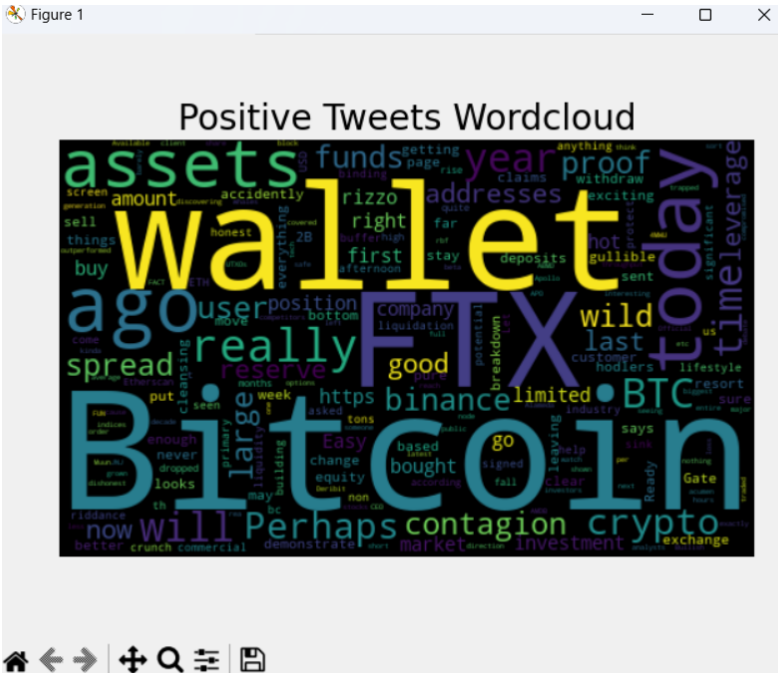


Fig. 4.16: Positive Tweets Word Cloud

Negative tweets displaying using word cloud

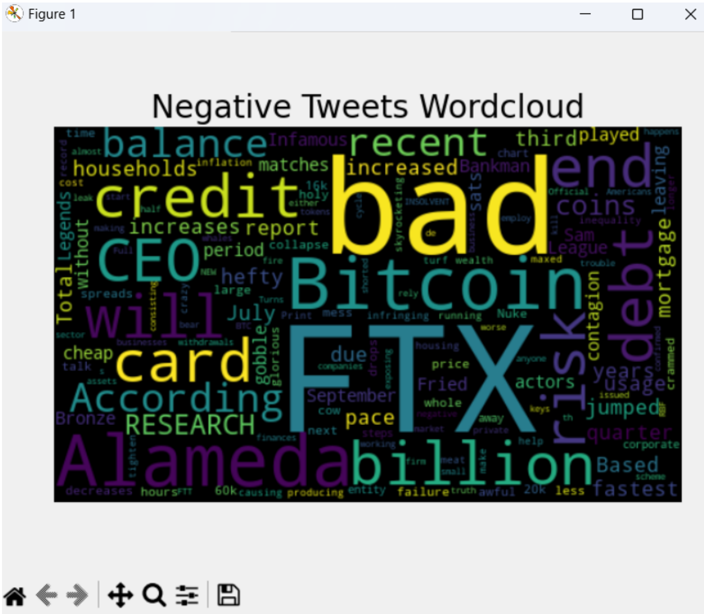


Fig. 4.17: Negative Tweets Word Cloud

Sentiment Analysis of Tweets

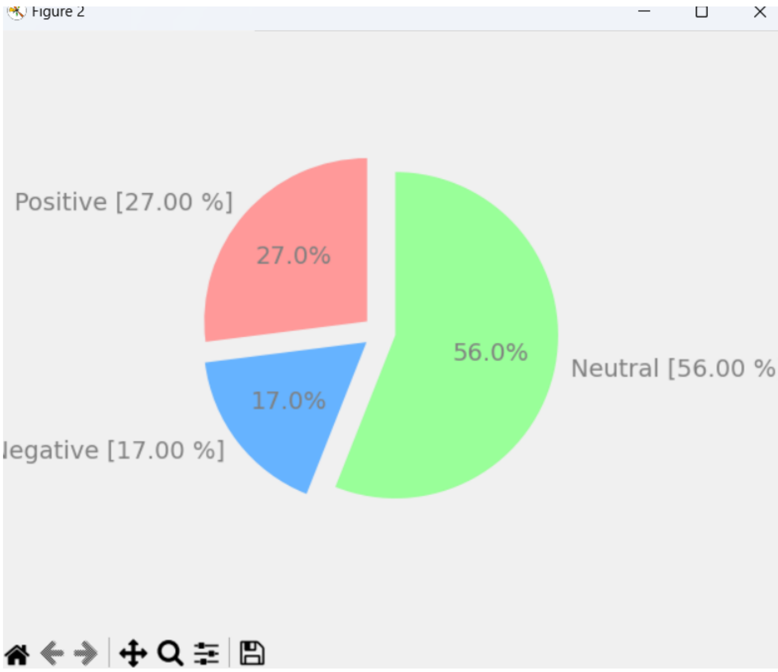


Fig. 4.18: Pie Chart of Sentiment Analysis

Chapter 5 Conclusions

The optimised implementation of Machine learning and Deep learning models was performed over five datasets of different crypto currencies. A comparative analysis was performed on the results of the models. The execution of the data preprocessing and filtering gave a clear and precise dataset to work on.

5.1 Applications

This project has got many applications worldwide and can be utilised by many people effectively.

1. It can be used by traders to check for the forecast and have a better understanding of what is going to be the direction of the cryptocurrency.
2. It can be used by investors who want to invest in digital currencies.
3. It can be used by people to understand the direction and trend of the cryptocurrency they are looking for
4. It can be used to understand the sentiments of the market and how it can affect the prices of the cryptocurrencies.
5. It can be used by people to understand the trend of the cryptocurrency but they should take investment and trading decisions based on their own conscience, it should not be considered as the only source of information and trust.

5.2 Future Scope

This project can be useful for everyone in the world who is interested in trading and investing in crypto currencies. A web application can be made and this project can be listed on different trading research platforms like trading view. Thus the traders can use a future prediction of the crypto currencies which they are interested in. Also, more technical indicators can be applied over the prediction part and thus making the predictions more versatile and changing the basis and dimensions of it.

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