Unveiling Ethereum's Future: LSTM-Based Price Prediction and a Systematic Blockchain Analysis

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Abstract. Cryptocurrency has emerged as a revolutionary innovation that has been replacing traditional finances and enthralling the worldwide technology landscape. This has gained a lot of popularity worldwide for its potential to enable peer-to-peer transactions and offer opportunities for investment and novelty. Nevertheless, it gives rise to issues concerning regulatory adherence, instability, and security apprehensions, turning them into a topic of continuous evaluation and investigation within the fields of finance and technology. This research paper presents a comprehensive exploration of the historical evolution of “Ethereum” as one of the leading blockchain platforms, with a primary focus on price prediction using a long-short-term memory (LSTM) machine learning model. The study includes various critical aspects of Ethereum, starting from its historical evolution to its potential future scope in scaling solutions and payments, and also covering the insights of Ethereum’s tokenomics, utility, and beyond. In addition, the methodology involves using the LSTM model to analyze data from Ethereum. The accuracy of price predictions is assessed by evaluating error metrics and further improved by visualizing the data through graphs that show indicators. This paper gives an in-depth perspective for anyone who is seeking a holistic understanding of cryptocurrencies, mainly concentrated on Ethereum, and also provides valuable guidance to investors, developers, and enthusiasts, encouraging them to make knowledgeable decisions in the ever-changing blockchain ecosystem.

1 Introduction

The surge in cryptocurrencies and blockchain technology has made a tremendous change in how money and technology can be tackled. Blockchain technology, probably known as the elementary ledger system of cryptocurrencies, has grown into a versatile and trusted mechanism for registering and upholding transactions. Its use cases have expanded beyond digital currencies, with blockchain utility in supply chain management as well as other sectors in finance. According to The History of “Bitcoin”, it's known that it was introduced by an anonymous entity named “Satoshi Nakamoto” in 2009. Since Bitcoin's beginnings as a whitepaper, it has become a widespread phenomenon among many technologists and economists. However, investing in the cryptocurrency market can be quite challenging, due, to its unpredictable nature. Many researchers have utilized machine learning techniques to predict the cryptocurrencies worth[29]. Among these digital inventions, Ethereum distinguishes itself as a remarkable blockchain platform that has expanded the horizons of decentralized applications and smart contracts. In the blockchain world, various models have emerged to evaluate performance and vulnerabilities. These models are essential for assessing efficiency and identifying potential threats in blockchain applications [30]. [31] This research paper explores the intersection of the Ethereum blockchain and machine learning, offering a promising path for addressing security and privacy challenges in 5G and B5G networks. By harnessing their collective potential, it seeks to revolutionize IoT environments and beyond.

This research embarks on Ethereum’s evolution, tracing its growth from the beginning to its current prominence. Expanding the focus [32], this paper delves into the transformative intersection of blockchain and AI as a combined impact on the Internet of Things (IoT). The objective is to find out how this fusion can drive the development of intelligent and secure IoT models. The keen observation of market dynamics involves trends in market capitalization, Total Value Locked (TVL), and unveiling its path of expansion. Additionally, the paper examines Ethereum’s economic structure by breaking down the tokenomics and disclosing the innovative “gwei” concept, along with the inner workings of mining and the utility of the native token, alongside an in-depth review of the functioning of decentralized applications, smart contract uses, and non-fungible tokens that have transformed sectors of blockchain.

Furthermore, this study explores Ethereum's consensus mechanisms by looking over the concepts of Proof of Work (PoW) and Proof of Stake (PoS) through Ethereum 2.0 and its involvement in exchange-traded funds (ETFs) and its position in bull and bear market trends. In addition, it introduces the visionary minds behind Ethereum's development and also covers its future scope, including scalability solutions and its role in payment systems. This paper mainly focuses on predicting the future price of Ethereum using machine-learning algorithms like LSTM, which is popularly known as the most accurate model for time series forecasting, and also provides readers with a profound understanding of Ethereum and its sophisticated ecosystem.

2 Literature Review

The theory of digital currencies is not entirely novel, but its successful implementation has been an achievement. In Chaum's paper, he introduced an ideology of untraceable electronic communication, including features like keeping sender identities hidden and offering public key cryptography-based digital anonymous identities [1] [22]. Importantly, his approach eliminated the need for centralized authority, allowing communication to remain anonymous. In a centralized way, banks and trusted authorities can prevent the simultaneous occurrence of transactions, which is a concern of significance, whereas in decentralization, this issue carries importance [2]. Here, the users have to maintain the P2P network. Consequently, this helps prevent potential attackers from undermining the system by introducing inaccurate or false information. Various techniques are used to improve the accuracy of price prediction using different machine learning models, such as LSTM and RNN, which are widely used for time series forecasting. A study by V. Kumar et al. [3] [24] demonstrated the efficiency of LSTM and RNN models. It also focuses on the influence of external factors, such as virtual entertainment and tweets, on cryptocurrency prices, which could further improve predictive capabilities in this dynamic market. The study by Karthik Vikram et al. [4] shows an interesting contribution to the application of data science processes and machine learning techniques. This paper consists of a market forecast for cryptocurrency prices using a range of machine learning algorithms, including random forest (RF) regression, linear regression, Ridge regression, logistic regression, and LASSO regression. Their findings reports an exceptional price forecasting model with an accuracy of 97.49%. This research confirms the effectiveness of data science in this particular application and prompts fascinating questions about the selection of regression methods for predicting cryptocurrency prices. The utilization of deep learning techniques has emerged as a prominent avenue of exploration in cryptocurrencies.

A study conducted by Emmanuel Pintelasl et al. [5] encloses the deployment of various deep learning architectures, including LSTM (long short-term memory), deep residual networks (DRN), Deep Neural Networks (DNN), to develop a robust cryptocurrency price prediction algorithm. The dataset taken from www.kraken.com served as the foundation for their analysis, leading to a remarkable conclusion: a prediction accuracy rate of 95%. Moreover, this research makes a meaningful contribution to understanding and sets the stage for improving the accuracy of predicting cryptocurrency prices using deep learning methods. The research conducted by Sina E. Charandabi and Kamyar Kamyar, published in Business and Economic Research in 2022 [6] [26], explores sentiment analysis techniques within the domain of machine learning. Specifically, numeric data from printed sources is transformed into a format suitable for analysis and subsequently integrated into a Multi-Layer Perceptron (MLP). This approach demonstrates an effective way of handling artificial neural network (ANN) techniques, including random forest and support vector machine (SVM), ultimately resulting in an overall prediction accuracy rate of 95%. It also adds a point towards the potential of combining textual sentiment analysis and ANN techniques to enhance forecasting capabilities in the cryptocurrency market. The study by Siti Saadah et al. [7] [25] presents the application of intelligent techniques, including Support Vector Machine (SVM), K-Nearest Neighbours (KNN), and Long Short-Term Memory (LSTM), with a specific focus on XRP, achieving an impressive prediction precision rate of approximately 80%. It offers valuable information for financial decision-makers and stakeholders. In the domain of Ethereum (Ether) price prediction, Politis et al. [8] explored advanced deep-learning models for forecasting Ether's price movements in 2021.

In a separate study, Jiayun Iuo et al. [9] employed techniques such as Random Forest (RF), Decision Tree, Support Vector Machine (SVM), and AdaBoost to improve cryptocurrency price prediction accuracy. Collectively, their findings indicate significant enhancements, with Decision Tree achieving 95% accuracy and AdaBoost surpassing this with an impressive 97.5% accuracy. These studies together highlight ongoing advancements in utilizing machine learning and deep learning models to enhance the precision of cryptocurrency price predictions. Hamayel and Owda presented a model utilizing bi-LSTM, LSTM, GRU, and machine learning algorithms, as documented in [10] and [23]. Their research introduces innovative methodologies, aiming to forecast crucial decision points for buying or selling cryptocurrencies. It's important to note that the actual traded prices may not precisely align with the corresponding moving average values, emphasizing the dynamic and complex nature of cryptocurrency markets. The reliability of gas price oracles, which provide critical information about transaction fees and confirmation times, is of utmost importance. Pierro et al. [11] carried out a case study using EthGasStation to investigate the reliability of these oracles, particularly about the reliability of EthGasStation. The analysis revealed that the margin of error for this particular oracle was noticeably larger compared to its initial claims, shedding light on the need for a more critical examination of the reliability of such tools within the blockchain ecosystem. The assessment of mining power decentralization has emerged as a crucial concern. L. Zeng et al. [12] presented a substantial analysis focusing on Ethereum's mining pool participants, providing a comprehensive and longitudinal examination of Ethereum's mining power decentralization. They also discussed comparable research involving the users of other significant blockchains, like Bitcoin and Ethereum, which underscores the need for a broader understanding of the decentralized mining landscape across various blockchain networks.

In the domain of Ethereum smart contract security, S. S. Kushwaha et al. [13] conducted a comprehensive systematic review. They evaluated and classified 86 security analysis tools for Ethereum blockchain smart contracts into two categories: static as well as dynamic analysis types.These hybrid tools demonstrated remarkable effectiveness, detecting over 95% of security issues. One important finding of this review was the widespread presence of the're-entrance' vulnerability, a critical concern in the context of Ethereum smart contracts. This vulnerability allows an attacker to repeatedly re-enter a contract, potentially leading to unauthorized access and financial losses. The findings of this study give important information that can help tackle the changing problems and offer crucial advice for making Ethereum smart contract analysis tools better and more effective in the future. The emergence of non-fungible tokens (NFTs) has been a transformative development in blockchain technology. A. Konagari et al. [14] in their research explore the application of the ERC721 token standard to create an NFT (non-fungible tokens) marketplace for blockchain-based digital assets. NFTs, being unique digital tokens, have witnessed a surge in popularity across various domains in current culture. The concept of NFTs has been leveraged to establish a 'chain of evidence,' ensuring the ownership and integrity of digital assets. Ethereum's blockchain has served as a validation space for demonstrating this notion of transmission along with the management of digital ownership, underscoring the important role of NFTs in this domain. This study plays a vital role in advancing applications, offering valuable insights into decentralized ecosystems for buying and selling NFTs.

In the Ethereum 2.0 domain, the study by M. Cortes-Goicoechea et al. [15] offers a clear analysis of resource usage within Eth2 clients. Ethereum's transition to Eth2 involves multiple development teams attempting to create functional software to support the shift. This study investigates Eth2 clients' resource usage at this scale, demonstrating the potential for identifying nonfinality periods through resource monitoring. Also, in the future, Ethereum 2.0 will remain a central focus in blockchain research, with an emphasis on resource efficiency and network stability. In the context of Ethereum 2.0 “The Merge,” the study by Z. Ouyang et al. [16] represents a brief overview of Proof of Work (PoW) and Proof of Stake (PoS) protocols, their features, limitations, and related improvements and applications. The study highlights that ongoing research is exploring ways to merge these protocols to achieve the goal of low-cost, secure, and fair consensus mechanisms. This shows the dynamic nature of blockchain technology and its continuous evolution towards improved consensus protocols. The study by B. Casella and L. Paletto [17] introduced a cutting-edge approach to predicting cryptocurrency market stages using long-term forecasting based on on-chain data. This study stands out as the first to forecast on-chain data while demonstrating its practical application in statistical hedging strategies. With a focus on six specific on-chain time series, its methodology holds promise for a broader range of relevant on-chain metrics. In addition, the study aims to expand its dataset collection, providing a more comprehensive understanding of market phases. The study by M. Bez et al. [18] investigates Ethereum's scalability challenges and highlights that Ethereum's current version handles approximately 15 transactions per second, with throughput affected by block size and interval rather than the number of miners. The research identifies data partitioning strategies like sharding as potential solutions but notes their impact on decentralization. Ethereum faces scalability challenges as it strives to handle more transactions while maintaining decentralization and security. The study contributes to understanding these challenges and trade-offs in Ethereum's evolving ecosystem and seeks to accommodate more transactions while preserving core principles.

Samin-Al-Waseen et al. [19] examine Ethereum price predictions using time series data and statistical models such as ARIMA and LSTM networks. In the long run, LSTM networks are more efficient than ARIMA, and the hybrid-stacked two-way LSTM network is the most efficient model. The study recommends further research, including increasing data accuracy, tuning hyperparameters, and exploring improved algorithms to deal with market seasonality and outliers. Overall, the study helps improve Ethereum price prediction by demonstrating the potential of LSTM-based hybrid models to capture market dynamics. The study by D. K. Tejaswi et al. [20] predicted Ethereum prices using various regression and deep learning algorithms. The algorithms discussed include LSTM, LSTM+GRU, etc. Interestingly, LSTM emerges as the best-performing algorithm, achieving an accuracy measure of an R-squared score of 0.9655. This study shows that one particular algorithm, LSTM, is good at predicting Ethereum prices. It also gives a hint that there might be even better algorithms out there to make these predictions. So, in the future, researchers will keep exploring to find ways to make Ethereum price predictions even more accurate. By improving price predictions, investors can make wiser choices about buying, selling, or holding Ethereum, potentially maximizing their investment returns and minimizing the risk of losses.

3 Exploration of Key Themes

In the section on key themes exploration, it is apparent that Ethereum stands as a versatile and dynamic blockchain platform with a vast range of applications. Starting from decentralized finance to non-fungible tokens (NFTs), smart contracts to supply chain management, Ethereum has a diverse array of use cases. This section explores the broad spectrum of insights regarding Ethereum’s utility, showing how it has changed industries and stands as a leading edge of innovation across many sectors. Ethereum is creating new opportunities and making huge changes in the way blockchain and decentralized technology work.

A. History and Initial Development

In the world of digital currencies, With respect to market capitalization, Ethereum is ranked second after Bitcoin. Ethereum came into existence shortly after Bitcoin gained popularity. The founder, Vitalik Buterin, whose vision led to the creation of Ethereum, He initially published the whitepaper for Ethereum in November 2013. The primary objective of Ethereum is to establish a framework, for constructing applications. Ethereum focuses on scenarios where speed in development, security and seamless interaction between applications are crucial. It serves as the building block featuring a blockchain integrated with a programming language that enables anyone to create smart contracts and decentralized applications with personalized rules, for ownership transaction formats and state transitions. In early 2014, Ethereum gained significance when Vitalik Buterin presented the concept of a blockchain project to the public at a Bitcoin conference held in Miami, Florida. This was an important moment that marked the formal unveiling of Ethereum, which has unique capabilities beyond Bitcoin. The project raised funds via an ICO (initial coin offering) later the same year. An ICO is a fundraising method in cryptocurrency where the project sells a portion of their own token to people who want to invest in their project in exchange for capital by contributing Bitcoin as their investment, which can be useful to develop and grow. Ether (ETH) was sold at 0.31 USD on the Ethereum network to raise capital. The ICO happened in the middle of July 22 and September 2, 2014, and was remarkably successful, collecting more than $18 million worth of ETH in total. Despite the sale of ETH tokens in the ICO, holders had to stand by until the blockchain went live before they traded their assets. The Ethereum blockchain began functioning on July 30, 2015. Once the blockchain went live, their tokens were converted into usable Ether.

B. Ethereum Tokenomics

Tokenomics is the concept of understanding the relationship between the supply and demand characteristics of cryptocurrency. A project with well-balanced tokenomics is more likely to achieve long-term growth in the blockchain space. The main features of tokenomics include token supply, utility, analyzing token distribution, and incentive mechanisms. Many investors are attracted to deflationary tokens due to their potential for value appreciation over time.

A deflationary cryptocurrency is a type of currency that becomes more valuable as the supply decreases. This makes the coin more attractive, to investors, in the market. This is the reason why Ethereum is popular for its tokenomics, as it is a deflationary token that has token burns, which effectively remove a certain number of tokens from circulation, resulting in a decrease in total supply and potentially increasing the value of existing tokens. Token burns can be done through mechanisms like Gwei, which consumes a small amount of ether as a transaction fee to execute smart contract operations. Ethereum Tokenomics refers to the ecosystem and principles governing the Ethereum blockchain, its native cryptocurrency, Ether (ETH), and various tokens built on the Ethereum blockchain. Some of the main key aspects are:

1) Ethereum (ETH): The native token serves as both a digital currency and a utility token within the ecosystem. It plays an important role in securing the network with a consensus mechanism that includes PoW and PoS.

2) Smart Contracts: Ethereum supports smart contracts. These self-executing contracts provide a various range of decentralized applications and decentralized finance protocols. Developers pay gas fees in ETH to deploy and execute smart contracts.

3) Token Standards: Ethereum introduced token standards such as ERC-20 and ERC-721. These standards define rules for creating fungible (ERC-20) and non-fungible (ERC-721) tokens on the Ethereum platform.

4) EIP-1559: EIP-1559 is a significant upgrade to the Ethereum network that changes the fee market dynamics. It introduces a mechanism that burns a portion of the transaction fees, potentially reducing the overall supply of ETH over time.

C. Market capitalization, TVL, Supply, FDV

Market capitalization and TVL give knowledge of the current state of specific cryptocurrency and blockchain ecosystems, whereas supply and FDV help developers and investors analyze some important factors like availability and the potential future dilution of a token value.

1) **Market capitalization:** Market capitalization is used to measure the total value of a specified cryptocurrency circulation.

Market Cap = Current Price per Coin (or Token) × Total Circulating Supply.

Ethereum's market cap as of September 22, 2023, is $191,845,573,350. Cryptocurrencies with high market caps are potentially more stable compared to other tokens. This helps in determining its value and long-term prospects.

2) Total Value Locked (TVL): The total value locked is the number of tokens that are deposited and locked within decentralized finance (DeFi) protocols. TVL is a crucial indicator for evaluating the popularity and vitality of the DeFi market. DeFi TVL is highly volatile and can change rapidly. According to https://defillama.com/chains, there are 912 protocols on Ethereum with 363,869 active users, and the total value locked is $21.18b ($21,180,000,000,000).

3) Supply of Ethereum: Supply refers to the total quantity of a cryptocurrency that currently exists. It can have a significant impact on its value, scarcity, and overall dynamics.
a) Total Supply: Ethereum doesn't have a fixed supply like other cryptocurrencies. So the total supply of ether changes over time. As of September 22, 2023, the total supply of ETH is 120,228,095. Ethereum's total supply is dynamic and can experience a surge due to a mechanism called the "block reward".
b) Circulating Supply: Circulating supply is the number of coins that are circulating in the market.As of September 2023, the circulating supply is 120,228,095. It is an important factor for calculating Ethereum's market capitalization.
c) Max Supply: Ethereum doesn't have a predetermined maximum supply cap like Bitcoin (BTC), which has a 21 million cap. Surprisingly, Ethereum's maximum supply is infinite. The transition to PoS with Ethereum 2.0 is expected to significantly reduce the rate of new ETH issuance.
d) Inflationary Supply: The PoW (proof of work) consensus mechanism was historically employed by Ethereum, which has resulted in an inflationary supply. Miners were rewarded with new ETH for creating new blocks and validating transactions. With the transition to Ethereum 2.0, the issuance of new ETH is expected to decrease, thus resulting in Ethereum becoming a deflationary asset.
e) Deflationary Supply: Initially Ethereum had an inflationary supply when it first started. However with the shift, from proof of work to proof of stake and the implementation of the EIP 1559 protocol Ethereum has become a deflationary asset. This change has occurred by introducing the plan of burning a portion of the gas fees, per transaction altering the characteristics of the Ethereum token. This will significantly impact the value of the token in the future.

4) Fully Diluted Valuation (FDV): Fully Diluted Valuation is the equivalent of estimating the maximum value that a cryptocurrency project may achieve if all of its tokens are already traded on the open market. It gives investors a means to see beyond what is now accessible.
Fully Diluted Valuation = Token Price X Maximum Supply
Ethereum's fully diluted valuation as of September 22, 2023, is $191,845,573,350.

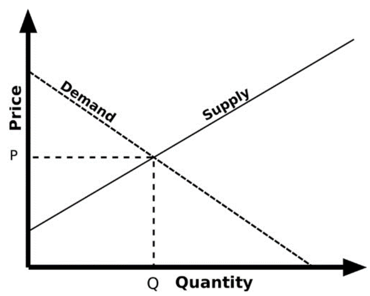

Fig. 1 : Demand Vs Supply (Source : Coingecko) [27]

D.The Consensus Mechanism
A consensus mechanism is any technique that promotes security, trust, and agreement between peers. Proof of work (PoW) and proof of stake (Pos) are the two most commonly utilized techniques in a blockchain.

1) The concept of GWEI: Gwei constitutes a pivotal denomination on the Ethereum network. Gwei fulfills a fractional role, denoting one billionth of a single ETH unit. It is the most commonly used as an ether unit.

2) Mining: Ethereum mining is the process where powerful computers, known as miners, solve computationally difficult tasks to check and record transactions on the Ethereum blockchain. The first miner to solve the puzzle gets rewarded with new Ethereum tokens (ETH) and transaction fees. Mining is vital for securing the network and creating new Ethereum. However, Ethereum is gradually shifting to a more energy-efficient method called proof-of-stake, which doesn't require the extensive computational power associated with traditional mining. Mining on the Ethereum network used to be something anyone with a regular computer could try, but not everyone could make a profit from it. There were expenses related to supporting the mining setup, like proper ventilation, energy monitoring, and electrical setup. According to [21], 'Ethash' is the only mining algorithm used by the Ethereum blockchain.

3) Proof of Work (PoW): Proof of work enables a secure peer-to-peer transaction without any third-party access. Large quantities of energy are needed for proof of work at scale, and this energy requirement only grows as more miners join the network. The act of mining entails validating transactions by resolving the hash in exchange for a reward. The hash needs to be verified before a new block may be opened following a closed block. The hash consists of a 64-character hexadecimal number that has been encrypted on the blockchain network. A hash for a significant amount of data may now be produced in milliseconds with the help of contemporary technologies.

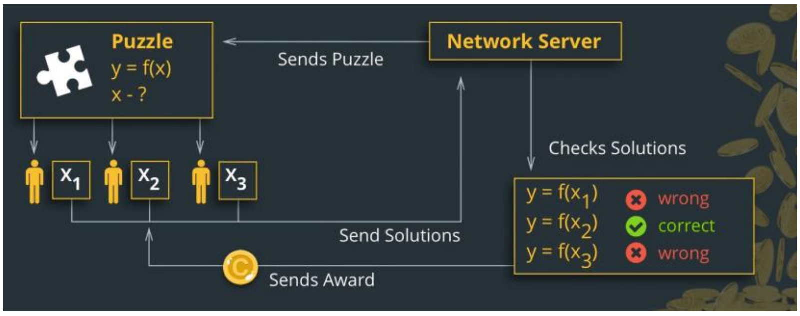

Fig. 2: Proof-of-Work Implementation (Source: Cointelegraph) [28]

4) Proof of Stake (PoS): In 2022, after the merge, Ethereum switched to a proof-of-stake system as it is thought to be less energy-intensive and offers a framework for putting novel scaling ideas into practice. PoS techniques demand validators keep and stake assets in exchange for the right to receive rewards. Validators are selected under proof-of-stake (POS) depending on the quantity of staked coins they own. The probability that a node with a larger stake position will be chosen at random to be the next block writer on the blockchain is higher. This reduced the computational power needed to verify transactions and blocks.

5) Ethereum 2.0 (The Merge): To address the scalability issues of Ethereum, Vitalik Buterin and his team have introduced a network upgrade known as Ethereum 2.0 or Eth 2. This upgrade brings changes to the foundation of Ethereum. Its implementation may take several years. Since 2020 dedicated Ethereum developers have been diligently working towards achieving a network upgrade that aims to make Ethereum faster more secure and more accessible, than before. The Eth2 upgrade is also referred to as the consensus layer upgrade. Through a phased approach involving the Beacon Chain, the Merge, and Shard Chains Ethereum intends to enhance scalability and security by making various infrastructure modifications. The transition from Ethereum state to version 2.0 involves many stages.

E. Smart Contracts

Smart contracts are programs that run on the Ethereum blockchain. They are digital agreements for crypto-based transactions. If certain conditions are met, then they can automatically execute transactions without the need for any third-party application. In traditional contracts, a written document contains terms and conditions governing a relationship between two parties (these conditions are legally binding or enforceable by law). That means both parties must follow the terms and agree to do what the contract says. Smart contracts, on the other hand, reinforce such agreements by encrypting the rules in software, enabling automatic enforcement without the need for third-party intervention. These play a major part in crypto as they provide a path to execute contracts in a secured and decentralized manner.

Although Bitcoin initially supported basic smart contracts, Ethereum is the one that showed great character by allowing developers to use the blockchain network to process more blockchain transactions. One of the key features of smart contracts is their immutability, which means that once they are put on a blockchain network, neither their code nor their rules can be altered or amended by anyone. Smart contract details such as blocks, transactions, and wallet addresses are found in EtherScan.This provides insights into transaction status, contract interaction, network statistics, etc. Some popular examples of smart contracts are lending apps, decentralized trading exchanges, and NFTs.

F. Utility

Ethereum has gained serious attention and utilization since its existence in 2015. Several cryptocurrencies exist, but to gain reputable value in the future, they must have good supply-side and demand-side tokenomics. Utility has an important role in the future perspective of the token. Ethereum has strong utility as its native token, Ether, is used for paying gas fees while executing transactions, staking ETH in protocols, and participating in DAOs (decentralized autonomous organizations) to get rewards. By holding ETH, it also provides access to a broad scope of decentralized applications (DApps) and DeFi services, improving its utility in the ecosystem.

4 Data Collection and Preprocessing

Ethereum (ETH-USD) data from January 1, 2016, to September 25, 2023, was collected using the Yahoo Finance API. To facilitate data analysis and model training, this valuable financial data was structured into a well-organized Pandas Data Frame, which provides an efficient and intuitive platform for data manipulation. As part of the preprocessing stage, the original date-based index was reset to allow for access and referencing using numerical indices. The 'Date' column, used as the index, and the 'Adj Close' column were dropped, leaving the data frame with essential features like 'Open,' 'High,' 'Low,' 'Close,' and 'Volume.' These preprocessing steps prepared the data for subsequent analysis and machine learning model development. These data collection and preprocessing steps involve analyses, including the development and validation of machine learning models like LSTM for price prediction.

Date	Open	High	Low	Close	Adj Close	Volume
2023-09-20 00:00:00	1,643.4954	1,649.6191	1,610.4208	1,622.8906	1,622.8906	5,156,431,986
2023-09-21 00:00:00	1,622.5918	1,625.2046	1,573.3058	1,584.307	1,584.307	5,191,732,312
2023-09-22 00:00:00	1,584.0026	1,601.5377	1,579.1013	1,593.2683	1,593.2683	3,460,791,634
2023-09-23 00:00:00	1,593.2131	1,598.0017	1,588.329	1,593.8578	1,593.8578	2,101,436,678
2023-09-24 00:00:00	1,593.8257	1,600.2073	1,576.7833	1,580.8534	1,580.8534	3,086,456,944

Fig. 3: Historical Ethereum (ETH-USD) Data (2016-2023)

5 Methodology

This study's main goal is to create, train, and evaluate a Long Short-Term Memory (LSTM) neural network for time series prediction. The LSTM model architecture is constructed as follows: A sequential model is created using the Keras library, a widely used deep learning framework. The model consists of a series of LSTM layers, each followed by dropout layers to overcome overfitting. The initial LSTM layer comprises 50 units, followed by subsequent layers with 60, 80, and 120 units, respectively. The Rectified Linear Unit (ReLU) activation function is consistently applied throughout the model. The final output layer consists of a single neuron. To enable model training, the LSTM model is compiled using the Adam optimizer, and the mean squared error (MSE) is selected as the loss function. The training process is a critical phase in which the model learns to capture patterns within the historical data. Training is executed over 50 epochs to iteratively enhance the model's predictive accuracy. Progress and loss convergence during training are visualized using loss curves.

Following model training, a detailed evaluation is conducted using various error metrics, including mean absolute error (MAE), R-squared (R2), mean squared error (MSE) and root mean squared error (RMSE). These metrics offer vital information about how well the model predicts the future, regarding Ethereum price prediction. Visualizations, including actual vs. predicted price charts over different time intervals, further aid in comprehending the model's forecasting capabilities. The methodology outlines the step-by-step process for conducting the study. It covers key aspects such as defining the model's architecture, specifying the training process, selecting appropriate evaluation metrics, and utilizing data visualization techniques.

6 Results

The Ethereum (ETH-USD) stock price forecasting study has produced important results and highlighted the accuracy of the approaches used. These results have been made clear through a thorough collection of visualizations and analytical evaluations.

A. Historical Price Trends

Figure 4 represents the historical price trends of Ethereum from January 1, 2016, to September 25, 2023, providing essential contextual information. The "Historical Price Chart" graphically illustrates Ethereum's long-term price trajectory.

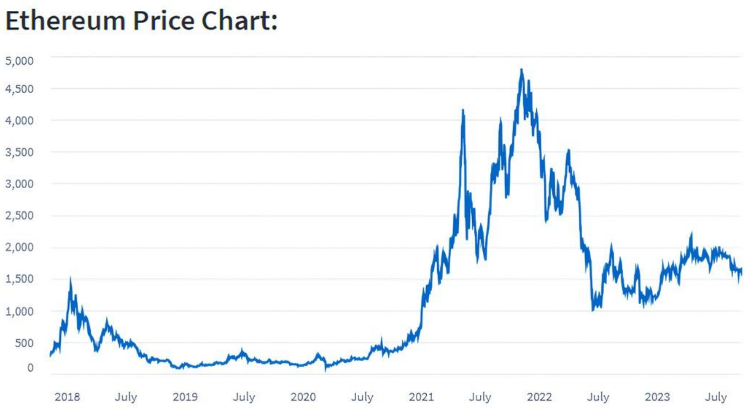

Fig. 4: Ethereum Price Chart

B. Technical Indicators:
The collection of technical indicators, including Moving Averages (MA), Exponential Moving Averages (EMA), the Ichimoku Cloud, and the Relative Strength Index (RSI), enriches the predictive model.

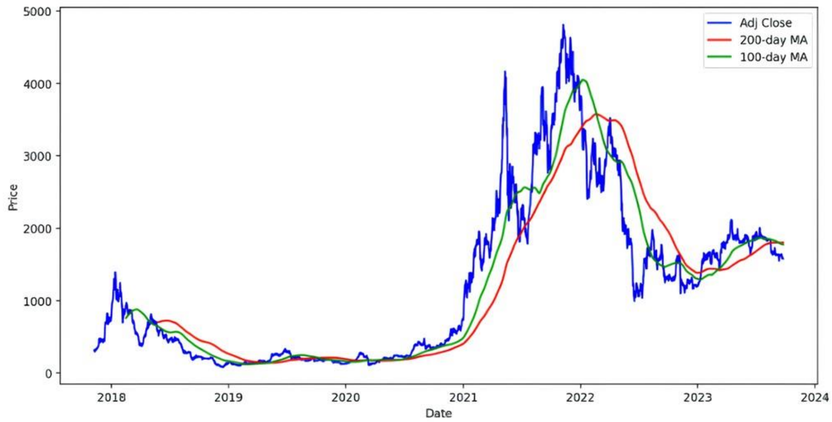

Fig. 5: Ethereum Price Chart showing Moving Averages

Figure 5 on the Ethereum price chart displays the interaction of short-term and long-term moving averages. This can help traders identify potential trends, make informed decisions regarding their Ethereum investments, and make price predictions.

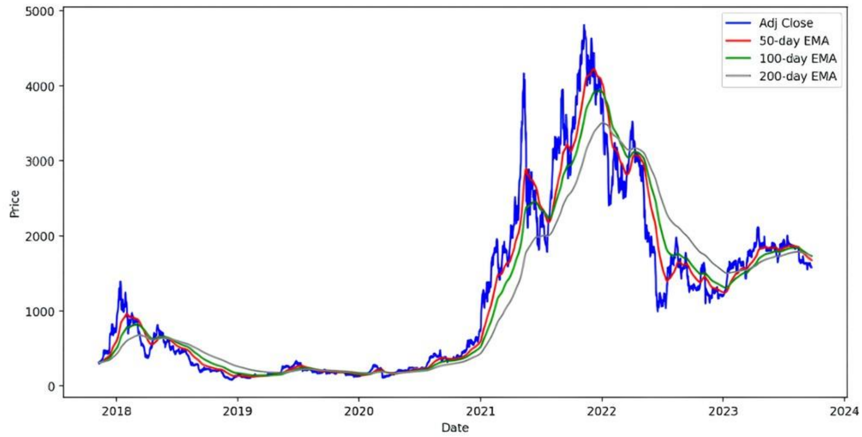

Fig. 6: Ethereum Price Chart showing Exponential Moving Averages

Figure 6 in the Ethereum price chart illustrates the Exponential Moving Averages (EMAs), which are used to analyze price trends by giving more weight to recent data points. This helps traders make predictions about future price movements.

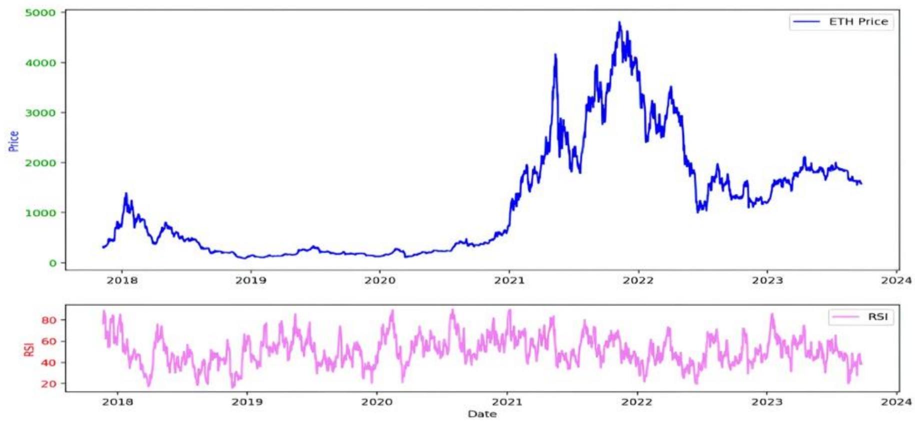

Fig. 7: Ethereum Price Chart with RSI

The Relative Strength Index (RSI), which quantifies the rate and direction of price changes, is shown in Figure 7 of the Ethereum price chart. It's a tool to gauge the overbought or oversold conditions of Ethereum.

C. Data Split:
In Figure 8, the "Training vs. Test Data Split" graph shows that for the LSTM (Long Short-Term Memory) model, 70% of the data is assigned for training the model, while the remaining 30% is allocated for testing the model's accuracy and performance.

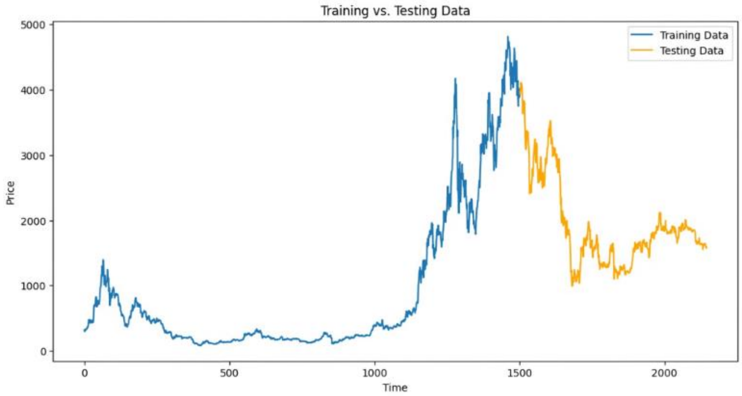

Fig. 8: Training vs. Test Data Split

D. Training Progress:
In Figure 9 ,The "Loss vs. Epoch" graph gives a clear view of the model's learning process. Over 50 training epochs, the model consistently refined its predictions, with a consistent decrease in training loss.

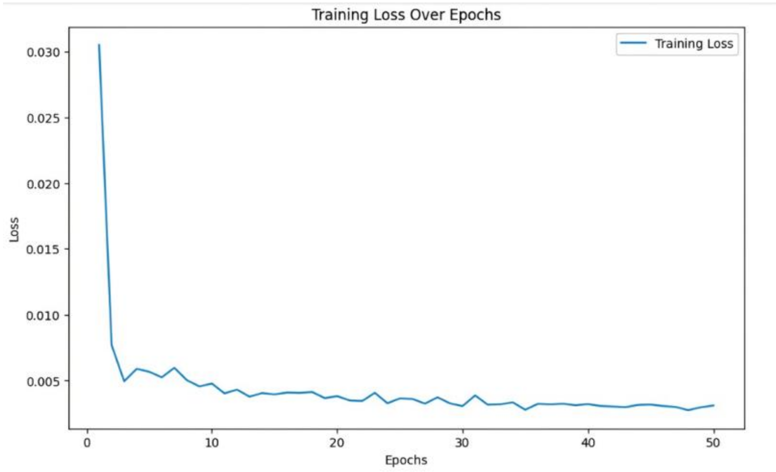

Fig. 9: Loss vs. Epoch

D. Predictions:
The LSTM model's predictive capabilities are a central focus. Predictions for varying timeframes—specifically, the last 100 days, 30 days, and 7 days—compared against actual prices reveal the model's adaptability to different forecasting needs.

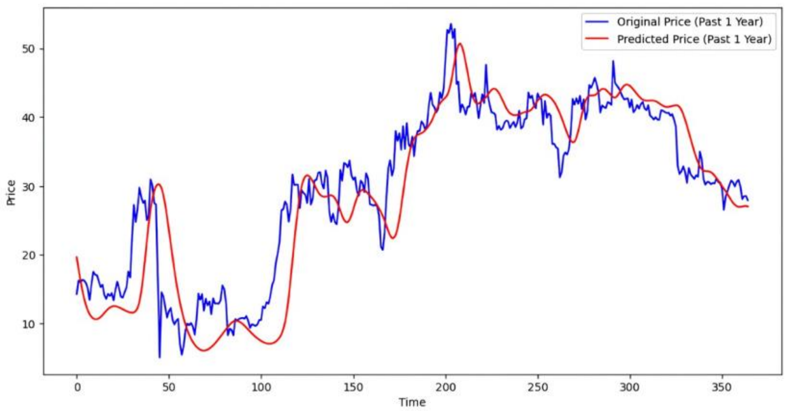

Fig.10: Original vs Predicted chart (Past 1 year)

Figure 10, the "Original vs. Predicted Chart (Past 1 Year)," compares the actual data from the past year with the predictions made by the trained LSTM model.

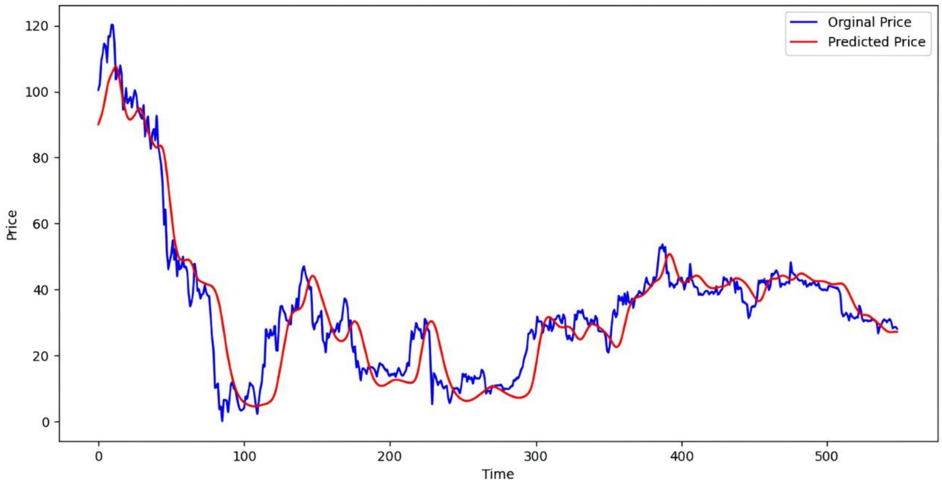

Fig 11. Original vs Predicted chart (Past 100 days)

Figure 11, the "Original vs. Predicted Chart (Past 1 Year)," compares the actual data from the past 100 days with the predictions made by the trained model.

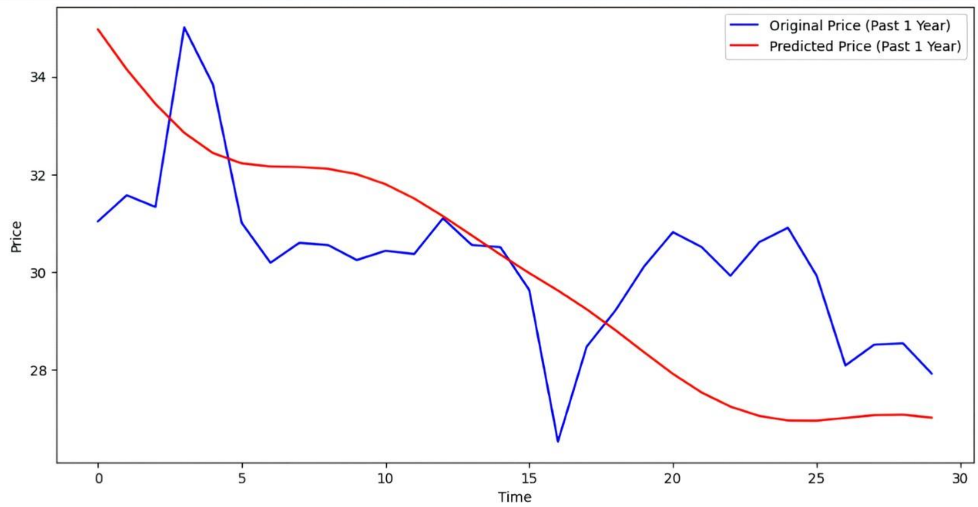

Fig. 12: Original vs Predicted chart (Past 30 days)

Figure 12, the "Original vs. Predicted Chart (Past 1 Year)," compares the actual data from the past 100 days with the predictions made by the trained lstm model.

E. Comparative Analysis:

Quantitative assessments of the model's accuracy were conducted using key error metrics, including mean squared error (MSE), root mean squared error (RMSE), mean absolute error (MAE), and R-squared (R2). These metrics are summarised in Figure 13: Metrics and Values of Errors to validate the model's robust performance.

	Metrics	Values
0	MSE	60.155794
1	RMSE	7.756017
2	MAE	5.406155
3	R2	0.884216

Fig. 13: Metrics and Values of Errors

7 Discussions

The LSTM model has demonstrated its reliability in predicting Ethereum prices, making it valuable not only in finance but also in engineering and blockchain. It's achieved through thorough assessment, strict training, and the incorporation of relevant technical indicators and around 88.42% of the volatility in the data is explained by the trained model. Looking ahead, LSTM models show promise, particularly if they can incorporate more parameters. This aligns with the growing demand for data-driven decision-making in engineering, where LSTM models can significantly enhance predictive accuracy and contribute to more efficient and dependable systems. Nevertheless, it's essential to remain vigilant for potential drawbacks and continually refine these models to meet evolving technological demands.

8 Conclusion

In conclusion, by exploring an unbelievable trajectory of growth and innovation, Ethereum has established itself as a major blockchain platform with a wide range of applications. Its history shows how adaptive it is and how it might lead to the quickly evolving world of cryptocurrencies and decentralized technologies. The solid tokenomics of Ethereum, along with its switch to consensus mechanisms, highlight its potential for long-term viability and its progress as Proof of Stake for future stability and development. While Ether (ETH) continues to be the foundation of its ecosystem, the transformational power of Ethereum's smart contract capabilities has revolutionized several industries. Ethereum is positioned to utilize a greater influence on business, technology, and the larger blockchain environment as it continues to address scalability issues and engage in ongoing improvements, reaffirming its place as a key participant in this exciting and disruptive industry. It is crucial to conduct research within the Ethereum ecosystem to effectively tackle challenges and ensure its success. To improve scalability, Ethereum needs to invest in research and development efforts that will make it faster and more cost-effective for users. Furthermore, it is important to prioritize research on enhancing security measures to safeguard user assets and data as Ethereum expands its influence. Additionally, exploring interoperability solutions should be a focus for Ethereum, enabling collaboration with blockchain networks and fostering a more interconnected and efficient decentralized ecosystem. Research serves as the foundation for Ethereum's ability to adapt and flourish in the evolving realm of cryptocurrencies and decentralized technologies.

9 Future Scope

GameFi, Decentralized finance (DeFi), the Metaverse, non-fungible tokens (NFTs) and Web3 are a few of the extraordinary ideas that Ethereum has been at the forefront of. The upgrades by Ethereum's developers aim to make the network more sustainable, scalable, secure, and efficient for real-world applications. The Shanghai Upgrade in April 2023 was the most recent revision to Ethereum's plan. This upgrade, which also included EIP-4895, enabled ETH validators to release their network-staked ETH. Staked ETH and related rewards became available as a result, greatly enhancing ETH liquidity in the cryptocurrency market.

The third major Ethereum 2.0 upgrade stage, Danksharding, focuses on horizontal database scaling. With this improvement, the burden of managing the massive amounts of data created by Layer-2 rollups will be distributed. Danksharding, in contrast to the conventional sharding strategy, uses distributed data sampling among blobs to increase Ethereum's scalability, reduce data storage costs, and enable anyone to work as a validator. Enhanced security and greater decentralization will result from this improved accessibility.
Ethereum can only process 15 to 20 transactions per second at the moment.

A crucial first step towards getting the platform ready for a subsequent round of four enhancements aimed at achieving 100,000 transactions per second was the switch to proof-of-stake. The constant improvements made to Ethereum are intended to increase its security, scalability, and effectiveness for practical applications.

10 References

[1]. D. Chaum, “Untraceable electronic main, return addresses, and digital pseudonyms,” in Communications of the ACM, vol. 24, no. 2, pp. 84-88, February 1981
[2]. F. Tschorsch and B. Scheuermann, "Bitcoin and Beyond: A Technical Survey on Decentralized Digital Currencies," in IEEE Communications Surveys & Tutorials, vol. 18, no. 3, pp. 2084-2123, thirdquarter 2016, doi: 10.1109/COMST.2016.2535718.
[3]. V. Kumar T, S. Santhi, K. G. Shanthi and G. M, "Cryptocurrency Price Prediction using LSTM and Recurrent Neural Networks," 2023 2nd International Conference on Applied Artificial Intelligence and Computing (ICAAIC), Salem, India, 2023, pp. 1-5, doi: 10.1109/ICAAIC56838.2023.10141048.
[4]. Karthik Vikram, Nikhil Sivaraman and P. Balamurugan, "Crypto Currency Market Price Prediction Using Data Science Process", International Journal for Research in Applied Science & Engineering Technology (IJRASET) ISSN: 2321–9653; IC Value: 45.98; SJ Impact Factor: 7.538, vol. 10, 2022.

[5]. Emmanuel Pintelasl, Ioannis E. Livieris, Stavros Stavroyiannis, Theodore Kotsilieris and Panagiotis Pintelas, "Investigating the Problem of Cryptocurrency Price Prediction: A Deep Learning Approach", IFIP International Federation for Information Processing 2020.
[6]. Sina E. Charandabi and Kamyar Kamyar, "Survey of Cryptocurrency Volatility Prediction Literature Using Artificial Neural Networks", Business and Economic Research ISSN 2162–48602022, vol. 12, no.1.
[7]. Siti Saadah and A.A Ahmad Whafa, Monitoring Financial Stability Based on Prediction of Cryptocurrencies Price Using Intelligent.
[8]. Agis Politis, Katerina Doka and Nectarios Koziris, "Ether Price Prediction Using Advanced Deep Learning Models", 2021 IEEE International Conference on Blockchain and Cryptocurrency (ICBC).
[9]. Jiavunluo, "Bitcoin price prediction in the time of COVID-19", 2020 Management Science Informatization and Economic Innovation Development Conference (MSIEID).
[10]. Mohammad J. Hamayel and Amani Yousef Owda, "A Novel Cryptocurrency Price Prediction Model Using GRU. LSTM and bi-LSTM Machine Learning Algorithms", AI, vol. 2, no. 4, pp. 477-496, 2021.
[11]. Giuseppe Antonio Pierro, Henrique Rocha, Roberto Tonelli and Stéphane Ducasse, "Are the gas prices oracle reliable? a case study using the ethgasstation", Proceedings of the IEEE International Workshop on Blockchain Oriented Software Engineering (IWBOSE), pp. 1-8, 2020.
[12]. L. Zeng et al., "Characterizing Ethereum's Mining Power Decentralization at a Deeper Level," IEEE INFOCOM 2021 - IEEE Conference on Computer Communications, Vancouver, BC, Canada, 2021, pp. 1-10, doi: 10.1109/INFOCOM42981.2021.9488812.
[13] S. S. Kushwaha, S. Joshi, D. Singh, M. Kaur and H. -N. Lee, "Ethereum Smart Contract Analysis Tools: A Systematic Review," in IEEE Access, vol. 10, pp. 57037- 57062, 2022, doi: 10.1109/ACCESS.2022.3169902.
[14]. A. Konagari, H. P. Kusuma, S. Chetharasi, R. Kuchipudi, P. R. Babu and T. S. Murthy, "NFT Marketplace for Blockchain based Digital Assets using ERC-721 Token Standard," 2023 International Conference on Sustainable Computing and Smart Systems (ICSCSS), Coimbatore, India, 2023, pp. 1394-1398, doi: 10.1109/ICSCSS57650.2023.10169350.
[15]. M. Cortes-Goicoechea, L. Franceschini and L. Bautista-Gomez, "Resource Analysis of Ethereum 2.0 Clients," 2021 3rd Conference on Blockchain Research & Applications for Innovative Networks and Services (BRAINS), Paris, France, 2021, pp. 1-8, doi: 10.1109/BRAINS52497.2021.9569812.
[16]. Z. Ouyang, J. Shao and Y. Zeng, "PoW and PoS and Related Applications," 2021 International Conference on Electronic Information Engineering and Computer Science (EIECS), Changchun, China, 2021, pp. 59-62, doi: 10.1109/EIECS53707.2021.9588080.
[17]. B. Casella and L. Paletto, "Predicting Cryptocurrencies Market Phases through On-Chain Data Long-Term Forecasting," 2023 IEEE International Conference on Blockchain and Cryptocurrency (ICBC), Dubai, United Arab Emirates, 2023, pp. 1-4, doi: 10.1109/ICBC56567.2023.10174989.
[18]. M. Bez, G. Fornari and T. Vardanega, "The scalability challenge of ethereum: An initial quantitative analysis," 2019 IEEE International Conference on Service-Oriented System Engineering (SOSE), San Francisco, CA, USA, 2019, pp. 167-176, doi: 10.1109/SOSE.2019.00031.
[19]. M. Samin-Al-Wasee, P. S. Kundu, I. Mahzabeen, T. Tamim and G. R. Alam, "Time-Series Forecasting of Ethereum Price Using Long Short-Term Memory (LSTM) Networks," 2022 International Conference on Engineering and Emerging Technologies (ICEET), Kuala Lumpur, Malaysia, 2022, pp. 1-6, doi: 10.1109/ICEET56468.2022.10007377.
[20]. D. K. Tejaswi, H. Chauhan, T. J. Lakshmi, R. Swetha and N. N. Sri, "Investigation of Ethereum Price Trends using Machine learning and Deep Learning Algorithms," 2022 2nd International Conference on Intelligent Technologies (CONIT), Hubli, India, 2022, pp. 1-5, doi: 10.1109/CONIT55038.2022.9848000.
[21].https://ethereum.org/en/developers/docs/consensusmechanisms/pow/mining/
https://www.investopedia.com/terms/p/proof-work.asp
[22] D. J. K. Karahyla, N. Sharma, S. Chamoli, D. A. Shirgire, R. Kant and A. Chauhan, "Predicting Price Direction of Bitcoin based on Hybrid Model of LSTM and Dense Neural Network Approach," 2023 4th International Conference on Electronics and Sustainable Communication Systems (ICESC), Coimbatore, India, 2023, pp. 953-958, doi: 10.1109/ICESC57686.2023.10193561.
[23] A. K. Bhuyan, D. A. Naik, S. Sharma, A. Gehlot, A. Jafersadhiq and D. Kapila, "The Forecasting About Bitcoin and Other Digital Currency Markets: The Effects of Data Mining and Other Emerging Technologies," 2023 3rd International Conference on Advance Computing and Innovative Technologies in Engineering (ICACITE), Greater Noida, India, 2023, pp. 988-992, doi: 10.1109/ICACITE57410.2023.10183141.
[24] K. R. Rao, M. L. Prasad, G. R. Kumar, R. Natchadalingam, M. M. Hussain and P. C. S. Reddy, "TimeSeries Cryptocurrency Forecasting Using Ensemble Deep Learning," 2023 International Conference on Circuit Power and Computing Technologies (ICCPCT), Kollam, India, 2023, pp. 1446-1451, doi: 10.1109/ICCPCT58313.2023.10245083.
[25] V. Veeraiah, V. Suthar, A. Y. Reddy, O. Dahiya, M. Azam and M. Kumbhkar, "Evaluation of Block-Chain Transaction Accuracy using Neural Network Model," 2022 2nd International Conference on Advance Computing and Innovative Technologies in Engineering (ICACITE), Greater Noida, India, 2022, pp. 233-238, doi: 10.1109/ICACITE53722.2022.9823465.
[26] M. Saraswat, N. Kaur, Y. Singh Bisht, G. S. Reddy, M. Al-Taee and M. B. Alazzam, "The Use of Deep Learning and Blockchain for Predictive Analytics in Financial Management," 2023 3rd International Conference on Advance

Computing and Innovative Technologies in Engineering (ICACITE), Greater Noida, India, 2023, pp. 11- 15, doi: 10.1109/ICACITE57410.2023.10182503

[27]Coingecko:https://s3.amazonaws.com/assets.coingecko.com/app/public/ckeditor_assets/pictures/4416/content_demand_and_supply.jpg

[28]Proof-of-Work Implementation :https://cointelegraph.com/storage/uploads/view/f419f334124a1e6ae4f67c8f7a1e64f1.jpg

[29] Zuniga, E. W. V., Ranieri, C. M., Zhao, L., Ueyama, J., Zhu, Y.-t., & Ji, D. (2023). "Maximizing portfolio profitability during a cryptocurrency downtrend: A Bitcoin Blockchain transaction-based approach." Procedia Computer Science, 222, 539-548. DOI: https://doi.org/10.1016/j.procs.2023.08.192.

[30] Rico-Peña, J. J., Arguedas-Sanz, R., López-Martin, C. (2023). "Models used to characterise blockchain features. A systematic literature review and bibliometric analysis." Technovation, 123, 102711. DOI: https://doi.org/10.1016/j.technovation.2023.102711.

[31] Miglani, A., Kumar, N. (2021). "Blockchain management and machine learning adaptation for IoT environment in 5G and beyond networks: A systematic review." Computer Communications, 178, 37-63. DOI: https://doi.org/10.1016/j.comcom.2021.07.009.

[32] Bothra, P., Karmakar, R., Bhattacharya, S., De, S. (2023). "How can applications of blockchain and artificial intelligence improve performance of the Internet of Things? – A survey." Computer Networks, 224, 109634. DOI: https://doi.org/10.1016/j.comnet.2023.109634.