Cryptocurrency Time Series Forecasting Based on Ensemble and Deep Learning Algorithms: A Comprehensive Review

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Abstract—**Blockchain technology is considered a transformative innovation, offering decentralized, secure, and transparent solutions to various industries, with cryptocurrencies being its most famous application. The volatility and non-linear behavior of cryptocurrency markets pose significant challenges for predicting their prices accurately. Predicting cryptocurrency prices based on traditional statistical methods often fails to capture the market's complex dynamics. Therefore, the recent developments in artificial intelligence, especially in deep learning (DL) and ensemble-based approaches, have presented promising results. This study delivers a comprehensive literature review focusing on the application of DL and ensemble DL algorithms in cryptocurrency time series price prediction. The main DL models, such as long short-term memory (LSTM), gated recurrent unit, convolutional neural network, and recurrent neural network, are examined with a variety of time intervals and cryptocurrency types. Among the analyzed research works, LSTM was the most effective model by achieving the best performance in 10 studies, followed by ensemble-based models, which ranked second by being the best in five studies. The findings present that DL models and hybrid or ensemble configurations have obtained promising results. This review highlights the efficacy and significant potential of ensemble DL and its capabilities in cryptocurrency price trend forecasting, offering valuable insights for investors and researchers.**

Index Terms—**Cryptocurrency, Deep learning, Ensemble deep learning, Price prediction, Time-series**

I. Introduction

Cryptocurrencies, digital assets that operate on blockchain technology, have gained rapid growth and unprecedented global attraction. Their decentralized nature and security have caused a paradigm shift in the financial systems with huge implications across economics, finance, and technology. From bitcoin to other altcoins, cryptocurrencies have attracted the attention of investors due to the potential for high return opportunities in the cryptocurrency market (Dudek, et al., 2024). There are over 20,000 cryptocurrencies worldwide as of today. The market capitalization is estimated to be worth billions of dollars. However, the high levels of fluctuations and volatility of this market, as well as its complexity, pose a real challenge for the investors. This volatility in the market and the unpredictability in prices impose an insistent need for more accurate forecasting models that have the ability to help in predicting the price trends of cryptocurrencies (Shamshad, et al., 2023). For long, statistical methods were the main tool for price trend forecasting in the markets. However, these methods have some limitations and face difficulties with the cryptocurrency market due to the complexities of this market and its stochastic nature. Consequently, we need advanced approaches that can better analyze and understand the dynamics of the cryptocurrencies' time-series data (Amirshahi and Lahmiri, 2023). To overcome the mentioned limitations of the traditional techniques, researchers have turned to adopting machine learning (ML) models and, in particular, deep learning (DL) algorithms (Zhang, Cai, and Wen, 2024).

The developments in DL models have shown promising results in tasks related to time-series data forecasting, which has encouraged the researchers. The most successful DL models used in time-series data forecasting are recurrent neural networks (RNNs), convolutional neural networks (CNNs), and long short-term memory (LSTM) (Gunnarsson, et al., 2024). However, identifying the optimal single DL model is still an open question, as the single model approach might be prone to overfitting. In addition, each model might excel in a different aspect of the data. For this reason, recent studies suggest ensemble DL methods for more accurate forecasting results. Ensemble learning models combine multiple models and predict based on a consensus mechanism. It combines the strength of multiple algorithms and mitigates issues such as overfitting and poor generalization, which improves the reliability and accuracy

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of the forecasts (Oyewola, Dada, and Ndunagu, 2022; De Rosa, Felber and Schiavoni, 2024).

This review primarily intends to provide a detailed assessment of the research that utilized DL models, as well as ensemble DL algorithms used in forecasting cryptocurrency time series trends. Therefore, a comprehensive review has been conducted on recent research. Moreover, the algorithms and findings of each research are analyzed and extracted. The rest of our paper will be as follows: Section II introduces the background of blockchain, cryptocurrencies, artificial intelligence (AI), ML, ensemble technique, as well as DL and its types. Section III explains the methodology of the research. Section IV presents the results and discussions of the review. Finally, Section V provides the conclusion.

II. Background Theory

Blockchain is a revolutionary innovation that has been utilized in various industries recently due to its security, decentralization, and transparency. Unlike traditional databases, blockchain is a distributed ledger that operates without a central authority recording transactions in a secure, immutable, and transparent manner, relying on a network of distributed nodes validating and maintaining the records as shown in Fig. 1 (Enco, et al., 2024). Since the inception of Bitcoin in 2008, blockchain has gained popularity and has grown beyond cryptocurrencies to revolutionize other industries such as healthcare systems, logistics, and supply chain management, and various other domains (Nguyen and Chan 2024). In the coming paragraphs, we will try to delve into the core concepts of how blockchain technology works and its applications, specifically cryptocurrencies. In addition, we will explain AI and DL as well as the common algorithms used for forecasting time-series data.

A. Core Concepts of Blockchain Technology

The blockchain technology is built on some core concepts and characteristics, which are considered the foundation of blockchain, as shown in Fig. 2.

1. Decentralization means that there is no central entity that makes the decision, per contra the decision-making is distributed among multiple nodes that are connected via a network. Each node within the blockchain network holds a copy of the distributed ledger to ensure transparency and reduce the data manipulation risk. The distributed nodes synchronize the updates via a consensus mechanism. Decentralization enhances security as the data are distributed among several nodes, which eliminates the risk of data loss or data breaches; hence, the system is fault-tolerant. Moreover, decentralization ensures transparency, as all nodes can view and verify transactions (Abdullah and Ibrahim, 2019; Bouteska, et al., 2024).
2. Distributed ledger in blockchain technology means a decentralized database that records all the transactions. It is organized in blocks that contain a set of transactions. One of the characteristics of the distributed ledger is immutability, meaning once a transaction is recorded and confirmed, it becomes nearly impossible to alter or delete (Puthal, et al., 2018).
3. Cryptography is one of the cornerstones of blockchain technology. It provides the essential security mechanisms, which ensure immutability. The key cryptographic techniques in blockchain are hash functions such as SHA256 used in Bitcoin and public key cryptography, as well as digital signatures. There are many benefits of cryptography in blockchain, such as security, privacy, trust, transparency, and most importantly, immutability (Abdullah and Ibrahim, 2019; Jaquart, Köpke and Weinhardt, 2022).
4. Consensus in blockchain is a process by which the nodes of a decentralized network agree on the validity and the order of the transactions, as well as the current state of the ledger. It is used to ensure trust and consistency across the network without the existence of a central entity (Puthal, et al., 2018; Wang, Andreeva and Martin-Barragan, 2023).

B. Blockchain Applications

Blockchain technology has been adapted to various industries and has provided a variety of advantages due to its transparency, security, efficiency, and trust among stakeholders. The most famous blockchain application is cryptocurrencies, which can be described as virtual or digital forms of money that rely on cryptography in creating new units and securing transactions. They are a form of peer-to-peer system that relies on a decentralized system and operates independently (Abdullah and Ibrahim 2019). The first and most popular cryptocurrency was Bitcoin, which was founded in 2009 by Satoshi Nakamoto. Nowadays, there are thousands of other cryptocurrencies. They are used for digital

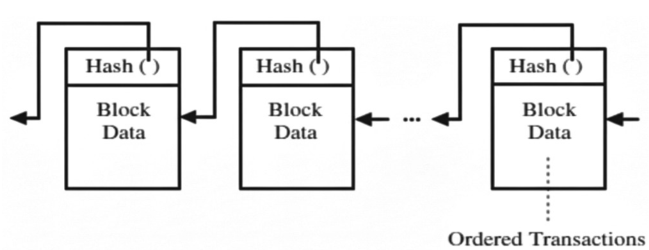

Fig. 1. Blockchain Structure (Abdullah and Ibrahim, 2019).

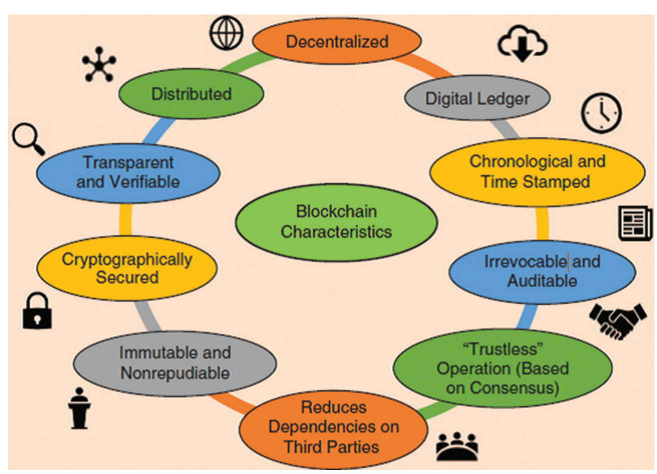

Fig. 2. Blockchain Characteristics (Puthal, et al., 2018).

payments and smart contracts. There are many advantages of cryptocurrencies, such as transparency, security, and low transaction costs. In addition, blockchain technology has many other applications, such as offering benefits to the supply chain management via enhancing transparency and increasing trust. The authorized participants can track and trace each product from raw material to the end customer. For instance, with luxury goods, it can verify the authenticity and provide provenance information to the consumers (Puthal, et al., 2018; Jing and Kang, 2024; Blasco, Sánchez and Garcia, 2024).

C. Time-Series Data

Time series data comprises a sequence of data points gathered in a specific chronological order over time within regular intervals, such as hourly or daily. These data points belong to a particular variable that evolves over time. These data can be analyzed to understand, analyze, and forecast future values and trends. The time-series data are used in many fields such as finance and weather (Agarwal, et al., 2022; Mirza and Al-Talabani, 2024).

D. AI

AI can be defined as the development of computer systems that have the ability to perform tasks that demand human intelligence, including spotting patterns and making decisions. It is an umbrella term that covers various technologies, including ML and DL. Usually, AI systems use algorithms and data. First, large datasets are collected and applied to the algorithms for training. Later, the algorithms are deployed to applications that adapt to new data (Shah, Vaidya and Shah, 2022; Rao, et al., 2023).

E. ML

ML is a branch of AI that makes predictions based on the learned data. Typically, the algorithm is trained on historical data, and then it is used to make forecasts based on new data. The algorithms learn the patterns and the relationships to make decisions and predictions. In general, there are three types of ML, which are supervised ML, unsupervised ML, and reinforcement ML. The first type, supervised learning, means the algorithm is trained using a labeled dataset. The algorithm learns how to map the input features to their output label. The second type, unsupervised learning, is not trained on labeled data; instead, it tries to discover the structure or the distribution in the data. The last type, reinforcement learning, learns using rewards and penalties for its actions (Siddharth and Kaushik, 2023; Ali and Abdulazeez, 2024; Pakizeh, et al., 2022).

F. DL

DL is a branch of ML and AI that originated from the artificial neural network (ANN). The term “Deep” refers to the concept of multiple stages of building data-driven models that can make intelligent decisions. The DL has considerable importance due to its powerful capabilities to learn from the given data. Moreover, its efficiency increases with the increase in the volume of the data (Siddharth and Kaushik, 2023). The way DL works is using multiple layers of data abstraction to build computational models, as shown in Fig. 3. It has a variety of applications in health care, cybersecurity, visual recognition, and time series forecasting. The DL uses types of neural networks to perform specific tasks. Below are some of the most popular types of DL techniques (Saeed, Abdulazeez, and Ibrahim, 2023).

1. CNN is a type of ANN that is primarily used in the analysis of visual imagery. This algorithm is utilized in tasks such as image recognition, segmentation, natural language processing, and other fields too (Sanjana, et al., 2024). A typical CNN comprises the following components: an input layer, convolutional layers, pooling layers, fully connected layers, and an output layer. Some of the challenges and limitations of CNN are high computational cost, large data requirements, sensitivity to adversarial attacks, and interpretability (Ibrahem and Abdulazeez, 2025; Sen, Rajashekar, Dharshan, 2023).
2. RNN is another type of ANN, which is mostly used in processing sequential data. It is effective in various tasks such as natural language processing, time series, and speech recognition. It is composed of three layers: an input

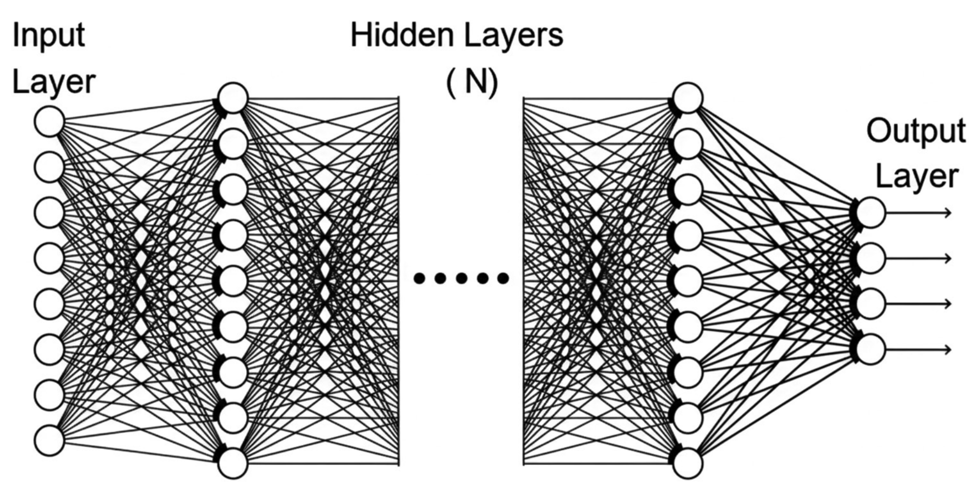

Fig. 3. Deep learning network (Sarker, 2021).

layer, one or more hidden layers, and an output layer. One of the challenges of RNNs is short-term memory, which is the struggle to retain information over long sequences, hence limiting its ability to capture long-term dependencies (Kochliaridis, Kouloumpris and Vlahavas, 2023; Khan, Khan and Shaikh, 2023).

3. LSTM is a type of RNN that is designed specifically to address the limitations of traditional RNNs, specifically the long-term dependencies problem. LSTM is commonly utilized in time series predictions, speech recognition, and natural language processing. The LSTM architecture introduces memory cells, which consist of a forget gate that discards parts of memory, an input gate that decides about the new information to be added to memory, and an output gate that takes control of the output of the memory and updates the hidden state. However, the limitations of LSTM are computationally expensive and require longer training times (Pratas, Ramos and Rubio, 2023; Ghadiri and Hajizadeh, 2025; Rafik and Shah, 2022).

G. Ensemble Technique

Ensemble learning is a technique that aggregates two or more individual models to produce more accurate predictions than an individual model. The ensemble technique helps to reduce bias and variance; thus, the error rate is reduced and the accuracy is increased. This technique, which is sometimes called hybrid decides based on majority voting. The ensemble technique has proven to have enhanced the results in many cases and increased accuracy as well (Kiranmai Balijepalli and Thangaraj, 2025; Nafea, et al., 2024).

III. Methodology

For this research, a literature review has been conducted by searching the most popular digital libraries, Science Direct, IEEE Xplore, Springer, and Scopus. The aim of the study is to review papers in the mentioned databases that are related to the utilization of DL algorithms and ensemble DL algorithms in forecasting the price trends of cryptocurrencies. The focus of this research was on the most recent papers. During the selection process, duplicate papers were removed, and the most relevant papers were reviewed. Finally, the algorithms as well as the findings of each research are analyzed and extracted.

IV. Results and Discussion

Cryptocurrency markets exhibit high volatility, which makes the process of forecasting an accurate price a challenging and crucial task for investors and researchers. Conventional statistical models have been extensively employed for time series prediction. However, they often struggle to capture all the complex dependencies and the dynamic nature of cryptocurrency price movements (Otabek and Choi, 2024). Therefore, with the advancements in DL, ensemble-based models that combine multiple neural network architectures have emerged as a promising approach for enhancing the accuracy of predictions (Akgun and Gulay, 2024). The review investigates prior research related to cryptocurrency time series prediction by focusing on the integration of DL models such as LSTM, gated recurrent unit (GRU), and transformer models within ensemble frameworks to improve predictive performance. By analyzing recent advancements, challenges, and comparative evaluations, the paper intends to illuminate the performance of ensemble DL algorithms for cryptocurrency price prediction. There have been many recent studies that have researched this interesting topic. The summary of the reviewed papers is presented in Table I, which contains the models used, the cryptocurrencies, and the time horizon, as well as the findings of the research. The study of He, et al. (2023) proposed an ensemble model consisting of ARMA-CNNLSTM, where the ARMA is used for modeling linear features, whereas the CNNLSTM is used for modeling non-linear ones. The performance metrics used by the authors were MAE, MAPE, and RMSE. In their study, daily bitcoin prices were used, and the findings of the study concluded that the predictive ability of this ensemble model was the best when compared with the baseline models. On the other hand (Li and Dai, 2020), used a hybrid model in their study. They utilized a variety of DL models, such as CNN, LSTM, and GRU, for predicting bitcoin prices using a 3-day price interval. Their study concluded that the results obtained from the hybrid CNNLSTM model were better than those obtained from a single neural network. Another study was carried out by (Sossi-Rojas, Velarde and Zieba, 2023) to forecast Bitcoin prices using ensemble DL technique. The study highlighted the importance of using GRU in the ensemble technique to improve the results. Moreover, another study was conducted by Livieris, et al. (2020), which used ensemble DL from LSTM, CNN, and BiLSTM models in addition to some other ML models to predict XRP, Ethereum, and Bitcoin prices on an hourly interval. They found out that the ensemble model is more effective and reliable, especially in periods when the volatility of the market is low.

Several other researchers tested a variety of DL models, such as (Aljadani, 2022), who applied GRU and LSTM to the daily prices of Bitcoin, Ethereum, and ADA, and their results showed that GRU was the best in cryptocurrency price prediction. Furthermore, Zahid, Iqbal, and Koutmos (2022) employed DL models and hybrid combinations for predicting bitcoin prices on several time horizons, and they concluded that the best-performing model was LSTM. In addition, Oyedele, et al. (2023) employed a CNN model and used Bitcoin, Ethereum, and other altcoins on a daily time frame interval for their research. They reported that CNN has obtained very promising scores for cryptocurrency price prediction. Furthermore, (Lopes and da Costa Bianchi 2022) utilized several DL models along with the ARIMA model. The cryptocurrency used in this research was Ethereum with a daily interval. They presented that DL models had superior results compared to ARIMA, and more specifically, CNN outperformed all other DL models in both accuracy and time.

Several other studies utilized RNN, GRU, and LSTM DL models, such as (Gunarto, Sa'adah, and Utama, 2023),

TABLE I
SUMMARY OF DEEP LEARNING MODELS USED IN CRYPTOCURRENCY PRICE FORECASTING

Authors	Year	Deep learning model	Cryptocurrency	Time frame	Findings and remarks
El Zaar, et al.	2024	CNN	ETH	4 H	High accuracy can be obtained by utilizing technical indicators, sentiment, and price altogether
Oyedele, et al.	2023	CNN, GRU	BTC, ETH	Daily	CNN has obtained very promising scores for cryptocurrency price prediction
He, et al.	2023	ARMA-CNNLSTM	BTC	Daily	The predictive ability of this ensemble model was the best when comparing it with the baseline models.
Gunarto, Sa'adah and Utama	2023	RNN, LSTM	BTC, ETH	Daily	LSTM outperformed RNN in predicting the price of both cryptocurrencies
Seabe, Moutsinga, and Pindza	2023	LSTM, GRU, BiLSTM	BTC, ETH, LTC	Daily	BiLSTM was the best-performing model in the price prediction, followed by GRU.
Murray, et al.	2023	LSTM, GRU	BTC, ETH	Daily	Among all the models, LSTM seemed to be the most effective in price prediction
Koosha, Seighaly, and Abbasi	2023	RNN, LSTM	BTC	Hourly	LSTM was better than RNN in Bitcoin price prediction
Tripathy, Hota, and Mishra	2023	LSTM	BTC	Daily	LSTM outperformed ARIMA with a minimized RMSE value
Sossi-Rojas, Velarde, and Zieba	2023	GRU, LSTM	BTC	Daily	The ensemble method based on GRU will enhance the results significantly
Liao, Lu, and Zhang	2022	LSTM	BTC, ETH, BNB, SOL, AVAX	Daily	LSTM was superior to machine learning and statistical models
Kang, Lee and Lim	2022	RNN, LSTM, GRU	BTC, ETH, XRP	Daily	GRU had the best performance among all other models
Lopes and da Costa Bianchi	2022	CNN, LSTM, GRU	ETH	Daily	CNN outperformed all other deep learning models in both accuracy and time
Aljadani	2022	LSTM, GRU	BTC, ETH, ADA	Daily	GRU's performance was the best in cryptocurrency price prediction
Zahid, Iqbal and Koutmos	2022	LSTM, GRU, BiLSTM	BTC	7 Days	The best performing model was LSTM
Jaquart, Köpke and Weinhardt	2022	CNN, RNN, LSTM, GRU	BTC, ETH, XRP	Daily	GRU and LSTM were the best DL models for forecasting cryptocurrency prices
Zakhwan, et al.	2022	LSTM, GRU	LTC, XRP	Daily	GRU was better than LSTM in predicting the prices of these two cryptocurrencies
Sarıkaya and Aslan	2022	CNN, LSTM, BiLSTM	BTC	Hourly	BiLSTM was the most effective and obtained the best results
Tavakoli, Doosti and Chesneau	2022	CNN, LSTM	BTC	Daily	LSTM was the best deep learning model in predicting Bitcoin prices
Gurkan and Palandoken,	2021	CNN, LSTM, BiLSTM, GRU	ETH	15 min	The best results were obtained using LSTM and BiLSTM
Jaquart Dann and Weinhardt	2021	LSTM, GRU, FNN	BTC	5 min	LSTM was the best-performing model with the highest accuracy rate
Li and Dai	2020	LSTM, GRU, CNN	BTC	3 days	Hybrid CNN-LSTM model provided the best results compared to a single neural network
Livieris, et al.	2020	CNN, LSTM, BiLSTM	BTC, ETH, XRP	Hourly	The ensemble model is more effective and reliable, specially in low volatility periods

CNN: Convolutional neural networks, LSTM: Long short-term memory, RNN: Recurrent neural networks, BTC: Bitcoin, ETH: Ethereum, GRU: Gated recurrent unit

who carried out their research using LSTM and RNN with the utilization of Ethereum and Bitcoin daily prices. In this research, RMSE and MAE metrics were used, and they concluded that LSTM outperformed RNN in the price prediction of both cryptocurrencies. In addition, Zakhwan, et al. (2022) conducted research in order to predict XRP and Litecoin daily prices. The performance metrics used by them were RMSE and MAPE, and they concluded that GRU was better in the prediction of these cryptocurrencies' prices compared to LSTM. Furthermore, Tripathy, Hota, and Mishra (2023) focused on Bitcoin only with a daily price interval, and the techniques used by them were ARIMA and LSTM. Their project consisted of two parts: the first one was to recognize Bitcoin daily patterns, whereas the second was to predict its daily price movements. They concluded that LSTM outperformed ARIMA with a less RMSE value. Moreover, (Koosha, Seighaly and Abbasi, 2023) researched the prediction of Bitcoin price forecasting based on an hourly time frame. They utilized RNN and LSTM, and the results presented that LSTM was better than RNN in price forecasting.

Several other researches have been conducted for the purpose of cryptocurrency price prediction, which utilized a variety of DL models and cryptocurrencies, such as (Jaquart, Köpke and Weinhardt, 2022), in which CNN, RNN, GRU, and LSTM models were employed. The cryptocurrencies used in the research were Bitcoin alongside the other top hundred cryptocurrencies, with a daily time horizon, and the results concluded that GRU and LSTM were the best-performing DL models. Seabe, Moutsinga, and Pindza (2023) also used GRU, LSTM, and BiLSTM in Bitcoin, Litecoin, and Ethereum daily price prediction, and the results showed that BiLSTM was the best performing model, followed by GRU. Similarly, Sarikaya and Aslan (2022) utilized various DL models such as LSTM, BiLSTM, CNN, along with some other ML models for

Bitcoin price forecasting, depending on an hourly timeframe. The findings of this study concluded that BiLSTM obtained the best results. In addition, Gurkan and Palandoken, (2021) utilized GRU, LSTM, CNN, and BiLSTM for predicting Ethereum prices over a quarter-hour timeframe. Although GRU obtained good results but the study concluded that the best results were obtained from using LSTM and BiLSTM. Likewise, Murray, et al. (2023) applied some ML and DL models to daily Bitcoin and Ethereum prices, and LSTM obtained the best results in price prediction. Moreover, (Kang, Lee and Lim, 2022) utilized ML models in addition to DL models in order to predict Bitcoin, XRP, and Ethereum daily prices. According to the results, among all the models, GRU was the best. Furthermore, (Tavakoli, Doosti and Chesneau, 2022) conducted a research to predict Bitcoin prices using daily price intervals. They applied several DL models and used accuracy and precision as performance metrics. The findings of the research presented that LSTM was the best DL model. Besides, (Jaquart, Dann and Weinhardt, 2021) utilized LSTM, CNN, and GRU and incorporated sentiment data, price data, and technical indicators as well. The model was applied to Bitcoin on various time horizons. The findings concluded that LSTM was the best-performing model with the highest accuracy rate.

In addition, some of the researchers used only a single DL model in their research, like (Liao, Lu and Zhang, 2022), who utilized LSTM, ML models, as well as statistical models to predict the price of several cryptocurrencies, such as Bitcoin, Ethereum, BNB, SOL, and AVAX on a daily time horizon. They concluded that LSTM was superior to ML and statistical models. In addition, El Zaar, et al. (2024) utilized a CNN model for the prediction of Ethereum prices on a 4-h scale. In addition to the price data, they used technical indicators and sentimental data. The results showed that high accuracy can be obtained by utilizing technical indicators, sentiment, and price together.

The review of existing studies on cryptocurrency price forecasting shows that DL models, particularly the ensemble technique, outperform traditional statistical and ML models. In addition, it highlights that individual DL models such as LSTM, GRU, RNN, and CNN have proven to be effective with superior performance in various scenarios. In addition, Fig. 4 summarizes the most used DL models in the reviewed studies, with the ranking of the best-performing model in each study. The results presented that LSTM was the most effective model by achieving the best performance in 10 studies, followed by ensemble-based models, which ranked second by being the best in five studies. Finally, the ensemble DL technique could be a promising approach for improving price prediction across different timeframes and cryptocurrencies.

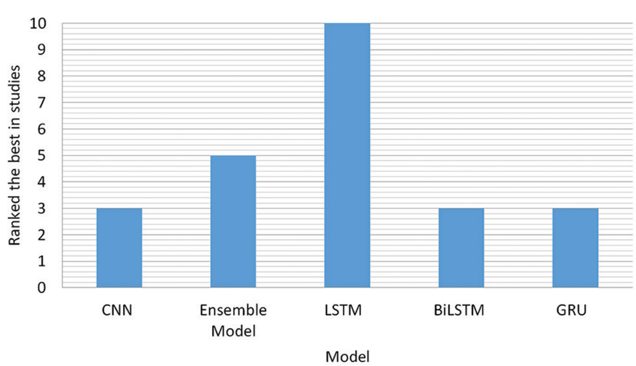

Fig. 4. Best performing models in the reviewed studies.

V. Conclusion

The increasing interest toward applying DL and ensemble-based techniques in cryptocurrency price forecasting reflects a considerable shift from traditional statistical methods, which often face difficulties in modeling the complexity and volatility of digital asset markets. In general, DL models such as LSTM, GRU, and CNN have demonstrated a notable success in capturing non-linear relationships and temporal patterns within cryptocurrency time series data. However, the performance of individual models may vary depending on different forecasting tasks and time intervals, as well as specific cryptocurrencies. The ensemble methods mostly produce more accurate and stable predictions. Therefore, integrating diverse models using an ensemble technique exploits the complementary strengths of each component and leads to enhanced generalization and improved robustness in dynamic market conditions. This paper highlighted the efficacy and the potential of DL methodologies in cryptocurrency price forecasting and the increasing relevance of ensemble strategies for a better predictive performance. Future studies can focus on exploring more advanced architectures, for example, Transformer-based models, which recently performed great in analyzing sequential data. Moreover, Explainable AI techniques can be utilized to enhance the transparency of the model, which in turn helps the investors as well as the researchers to understand the drivers behind model predictions and increase trust in AI-driven financial decisions. Furthermore, integrating multimodal data sources by combining indicators with social media data and news, as well as blockchain metrics, could be a promising direction to get a more detailed view of the dynamics of the markets. These emerging trends could further evolve the applications of DL in cryptocurrency forecasting and will help in further improving the accuracy and reliability of the predictions.

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