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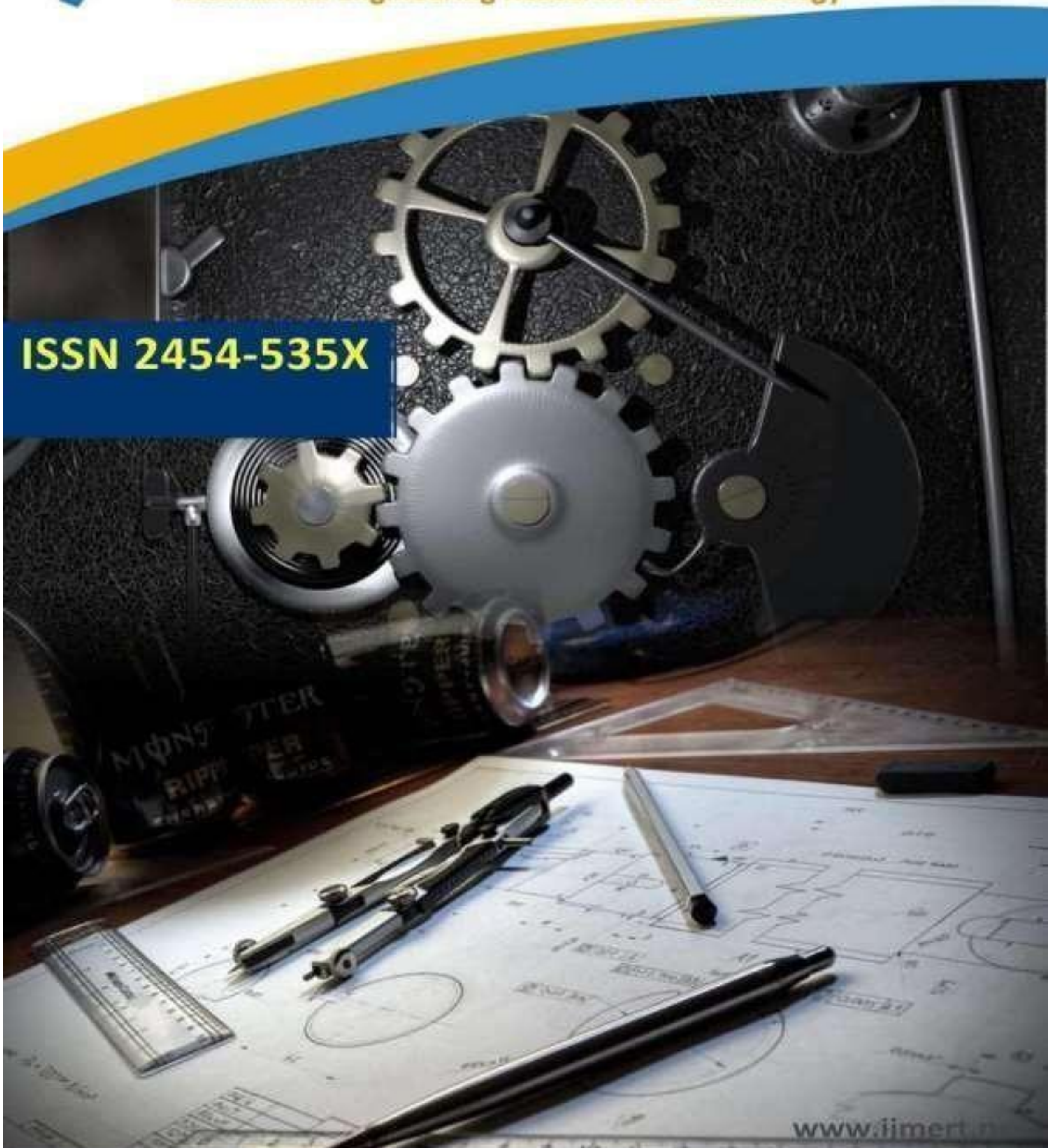

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Analyzing the Applications of Supervised and Reinforcement AI and Machine Learning Models in Cryptocurrency Price Prediction

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Abstract

Cryptocurrency markets account to over $2 trillion in terms of total capital in 2022, i.e., almost similar to market capitalization of Apple at the same time. Cryptocurrencies have been widely established in financial markets with huge sum of trades and transactions taking place every day. Like other fiscal systems, price prediction is a major challenge in crypto trading. Hence, "Artificial Intelligence (AI)" has been widely used to predict cryptocurrency prices and has become a well-known matter to study in cryptocurrency.

Unlike legacy financial models, machine learning (ML) models have shown great performance in finance. They are supposed to be best to deal with the problem of price prediction in the volatile and complex crypto market. A lot of studies have been conducted on machine learning for predicting movement and price as well as portfolio management. However, these models and approaches are in nascent stages. This study reviews existing research on reinforcement and supervised learning models to predict crypto prices. It also highlights potential areas to improve and research gaps to fill. Additionally, it focuses on potential research directions and challenges which will be interesting in machine learning and AI communities in crypto market.

Keywords: cryptocurrency, machine learning, artificial intelligence, supervised learning, reinforcement learning

1. Introduction

There has been a remarkable change observed in cryptocurrency markets quite lately both in public domain and statistical terms. Cryptocurrencies have capped $1.664 trillion in terms of market capitalization in March 2022, as compared to $267.8 billion in November 2017, according to

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Trading View (2022). Bitcoin has the highest market cap as the most popular cryptocurrency. When excluding it, the market cap of Altcoins grew to $1.007 trillion in 2022 from $86.31 bn in 2017. There is also a rise among foreign companies which have invested in crypto-based solutions. For instance, using Dogecoin to buy Tesla products is a great example. Hence, Cryptocurrency has been an established, popular phenomenon and it is widely integrated with other financial assets (Ciaian et al., 2016; Ji et al., 2018).

1.1 Background

Cryptocurrency has become the most common topic of interest for investors. A lot of small investors have speculated on cryptocurrencies and managed to have a small fortune. They use social media to follow trading updates. Meanwhile, investors might also lose money because cryptocurrencies are highly volatile. For example, the "market cap of Bitcoin had dropped to $935 billion from $1.18 trillion within just 10 days in April 2021 and almost halved to $602 bn in the next 3 months in July 2021, according to Coinmarketcap.com.

Hence, reducing investment risk is a serious concern in cryptocurrency markets. There is also a rise in number of promising approaches to predict existing trends and deal with cryptocurrency analysis. The behaviour of cryptocurrencies is a lot different from fiat currencies and they are highly volatile and uncertain for investors (Abraham et al., 2018). So, investors need to have different trading strategies. Several elements of price formation of cryptocurrencies are yet to be tested properly, making it the main cause of uncertainty. Hence, it is important to investigate further and gain deeper knowledge of crypto markets (Mittal et al., 2018).

Asset trading has been going through significant changes with the rapid growth in telecom and computing infrastructures which are supporting huge improvement in trading (Wu et al., 2020). Consequently, a lot of investors, transactions, and multiple data sources like tweets, hashtags, feeds, etc. on social media have led to a huge amount of data related to cryptocurrency markets

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over the years. Hence, investors have to look ahead of conventional methods and develop automated trading models to deal with such amount of big data. Fintech companies have transformed their trading strategies to manage big data in contrast with quantitative approaches used over the years. Fintech organizations have been established with integration of finance and AI (Dai et al., 2017). Artificial Intelligence (AI) has been a well known research topic as a key tool used by Fintech organizations in quantitative trading. It has been highly efficient to discover profitable routes for trading (Huang et al., 2019; Rasekhschaffe & Jones, 2019). As compared to other statistical tools, AI has become a promising tool for analysis to deal with complex environments (Chuen & Deng, 2017; Leong & Sung, 2018; Stulz, 2019).

2. Literature Reviews

Machine learning models are now capable to gather high-level patterns of financial market information. Deep learning models are used by investors to determine and calculate foreign exchange and stock markets with AI. There has been a propagation of application of reinforcement learning in trading. Combining trading signal and price prediction, DRL agents are used to build various trading strategies or systems that are completely automated. Sahu et al. (2023) conducted research on the use of "deep learning, machine learning, deep reinforcement learning in Quantitative Finance (QF), reinforcement learning, and stock market." They also discussed potential research directions in this domain.

Blockchain research is focused highly on cryptocurrency which has grabbed the attention of academics. Availability of bitcoin resources and big data promotes the use of machine learning (ML) models. However, comprehensive study and thorough analysis of ML is needed for further studies. Price prediction in cryptocurrency is a very important topic and different algorithms are widely used in cryptocurrency studies. A lot of studies have used various ML models. Mujlid

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(2023) conducted a study to predict cryptocurrency prices with machine learning and discussed existing research challenges in ML applications in cryptocurrency.

Awotunde et al. (2021) used machine learning models to build the model to predict cryptocurrency and stock market prices with technical indicators which are vital to study market trends. This study learned the adoption of "Long Short-Term Memory (LSTM)" model to develop the model to predict cryptocurrency prices. Some of the important factors they used are "close price, available price, low price, high price, market cap, and volume" with interdependencies related to cryptocurrencies based on measuring important features influencing unpredictability of trade with the application of model to improve the process effectiveness. Nevertheless, there is a lack of regulatory structures of the cryptocurrency market and it is not easy to predict. Hence, price forecasting is very complex and hard. It is observed that machine learning is very effective to predict crypto prices. LSTM model performed better than other models in terms of "Ether, Bitcoin, and Litecoin" cryptocurrencies. This model was efficient with 67.43% accuracy to predict cryptocurrency price.

Deep learning models have been brought as new frontiers lately and development is too rapid. Hence, Jiang (2021) conducted a review of recent studies on deep learning to predict stock market status. They categorized various data sources, widely-used metrics, and neural network models along with their reproducibility and implementation. The key here is to help researchers to sync with recent developments and reproduce earlier studies as baseline research.

Felizardo et al. (2022) explored both "reinforcement learning and supervised learning" models applicable to asset trading while seeking attention to the pros of both methods. This study goes beyond the comparison among both methods with advanced strategies. They proposed "ResNet architecture," one of the best "deep learning models" to conduct "time series classification" into "ResNet-LSTM actor (RSLSTM-A)." RSLSTM-A is compared against recent and classical

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"reinforcement learning techniques" like "deep Q-network, recurrent reinforcement learning, and advantage actor-critic." They simulated the environment of "currency exchange market" with "time series analysis of Ethereum, Litecoin, Bitcoin, Nxt, Monero, and Dash" cryptocurrencies for running the tests. They presented graphical illustration of features gathered from "ResNet neural network" to identify the characteristics generated by each block.

2.1 Research Gap

There have been various studies conducted on the economic and financial sectors like banking, insurance, and Fintech and their use of cryptocurrency markets. For example, Mosavi et al. (2020) studied deep learning models in several economic and finance sectors. Sabry et al. (2020) conducted a survey on existing opportunities and challenges of AI in various domains of cryptocurrency like crypto mining, volatility prediction, and fraud detection. Ozbayoglu et al. (2020) discussed state of the art of deep learning methods for different financial applications like risk management, algorithmic trading, behavioral finance, and fraud detection." Hence, this study fills the gap by discussing recent AI applications in cryptocurrency. It focuses on prediction of crypto prices by machine learning and gives detailed review of challenges in prediction of prices. In addition, it studies the financial aspects of price prediction in previous studies.

2.2 Research Question

- What are the applications of AI in cryptocurrency price prediction?
- How supervised and reinforcement learning models are used in cryptocurrency market?

2.3 Research Objectives

- To investigate applications of AI in cryptocurrency price prediction
- To review supervised and reinforcement learning models and their applications in cryptocurrency market

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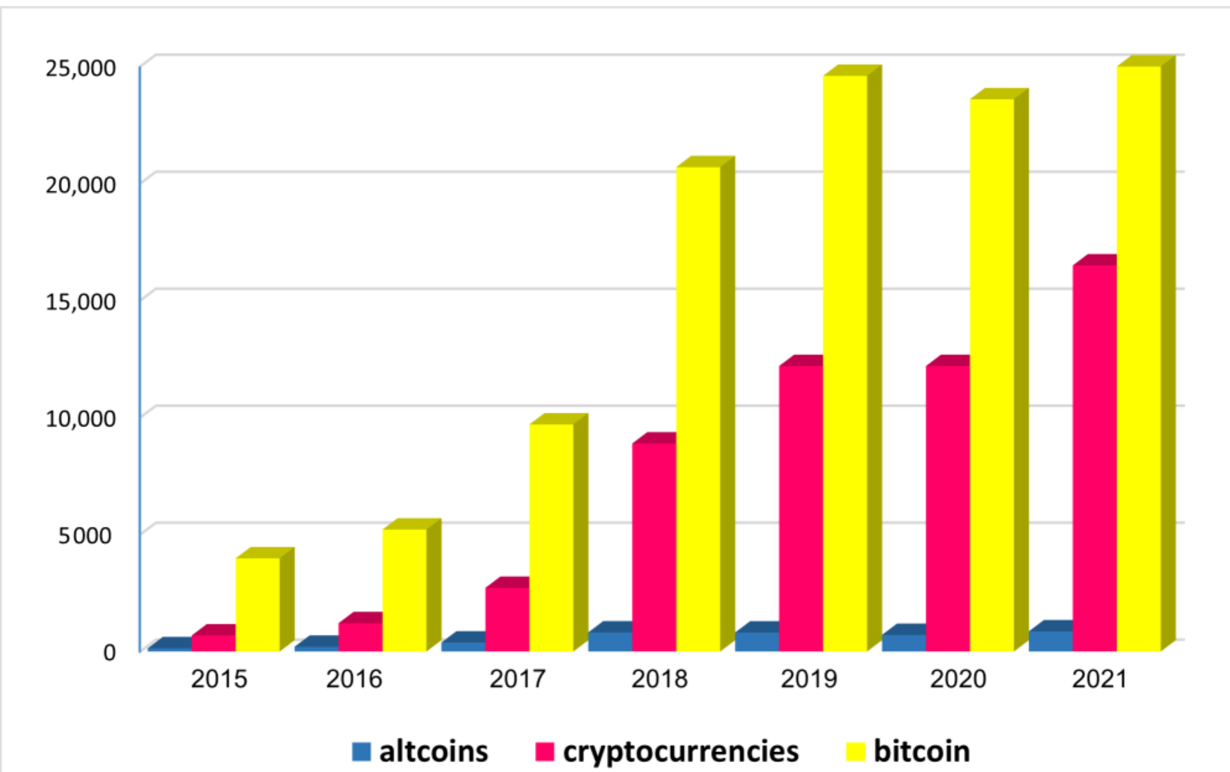
3. Research Methodology

There has been a rise in academic studies in cryptocurrencies related to domains like AI, finance, and economics. In this study, keyword search is conducted to find those studies in Google Scholar (Strobel, 2018). There has been a significant rise in number of studies related to keywords like "altcoins, altcoin, cryptocurrencies, and cryptocurrency" from 2015 to 2021 (Figure 1).

Figure 1 – Studies published related to cryptocurrencies from 2015 to 2021



Source – Amirzadeh et al. (2022)

On the other hand, in cryptocurrency trading, another potential category is related to systematic trading, trading programs, emerging technologies, market condition, and portfolio research (Fang

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et al., 2022). This study is based mainly on emerging technologies for trading like machine learning. Several studies have been published on applications of AI models in prediction of crypto prices.

4. Analysis of Study

4.1. Applications of AI in Cryptocurrency Price Prediction

Economic systems widely used third-party bodies like banks for payment processing. These institutions are mediators between parties to "exchange funds and they have absolute control in all transactions. Even though typical systems have conducted financial transactions, there are still some drawbacks. For instance, limits on the transaction amount, lack of trust, transaction costs, transparency, security issues, and flexibility are some of those drawbacks. There were several failed attempts to come up with "decentralized unregulated virtual currencies" to deal with these issues. Some of these problems were addressed by the invention of blockchain in 1991 by W. Scott Stornett and Stuart Haber (Al-Jaroodi & Mohamed, 2019). A block header having metadata like earlier block, timestamp, block version, hash, transaction data, and nonce is used in blockchain-based cryptocurrency system. It identifies a specific block in blockchain and there is a header dedicated to each block. Table 1 lists the attributes of information in a crypto blockchain and describes each item in short.

Table 1 – Attributes of information of a crypto-based blockchain system

Headers	**Information Attributes**
Crypto statistical data	Crypto price
	Total circulation – Total coins mined
	Market capitalization – Total crypto value being circulated
Block	Size of blockchain
	Average block size over the previous 24 hours
	Average transaction in each block over the last 24 hours
	Average confirmation time – Average time for adding mined block to public ledger

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Mining	Total hash – Calculated terahashes per second Distribution of hash rate – Calculation of distribution of hash rate among largest pool of mining Problem in network for mining a new block Fees for each transaction on average Revenue for miners – Total value of rewards as crypto block and transaction fees given to the miners

There are three different features making cryptocurrencies different – decentralization, anonymity, and protection from double-spending attacks (Lansky, 2018). However, ambiguity is still prevalent between cryptocurrency and electronic money even with these aspects. A clear difference between electronic and virtual currencies has been defined by the "European Central Bank (2012)" in Table 2. There is a difference in terms of acceptance, format, issuer, legal status, etc.

Table 2 – Difference between virtual currency and electronic money

Attributes	**Electronic Money**	**Virtual Currency**
Format	Digital	Digital
Legal Status	Regulated by central authority	Not regulated by any authority
Acceptance	By activities except the issuer	A dedicated virtual community
Supply	Fixed	Decided by the issuer
Issuer	A legally-established body	A private, non-financial organization
Risk type	Operational	Credit, legal, operational, liquidity
Supervised	Yes	No

Source – European Central Bank (2012)

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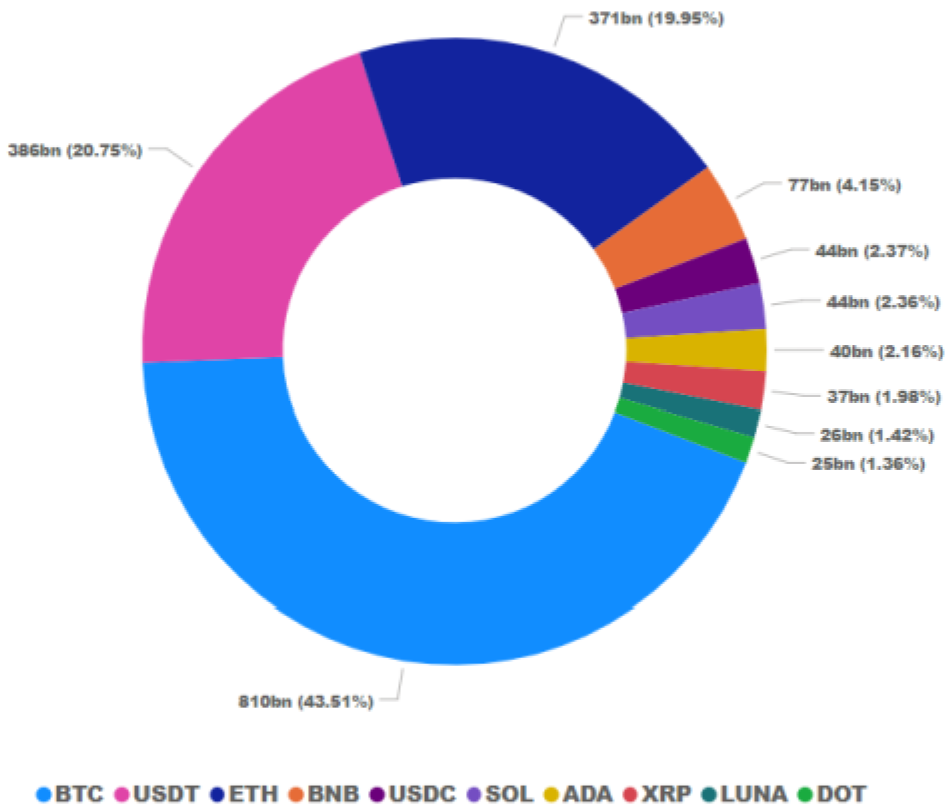
Bitcoin is the most popular and renowned cryptocurrency and *de facto* standard in crypto market. There are around 17,000 cryptocurrencies in the market known as altcoins, with over 50% of capitalization in the market. Figure 2 illustrates market cap of top 10 cryptocurrencies as per CoinMarketCap, as on January 2022. The figure illustrates cryptocurrencies like "Bitcoin (BTC), Ethereum (ETH), Tether (USDT), Binance Coin (BNB), USD Coin (USDC), Solana (SOL), Cardano (ADA), Ripple (XRP), Terra (LUNA), and Polkadot (DOT)."

Figure 2 – Market Cap of Top 10 Cryptocurrencies as on January 2022 as per CoinMarketCap



Source - Amirzadeh et al. (2022)

Cryptocurrencies are also split as per platform category, currency domain, and application (Patel et al., 2020). The ecosystem of cryptocurrencies relies mainly on several exchanges as they give

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investors with trading tools. Table 3 discusses several common exchanges as per their specifications. Number of cryptocurrencies available for trade are listed in “Number of Supported Coins” column. In addition, headquarters, transaction fees, and year of foundation are also mentioned. Transaction fees vary by exchange from 0% to 4% for each trade.

Table 3 – Number of Most Popular Crypto Exchanges

Crypto Exchanges	**Total supported coins**	**Transaction Fee (%)**	**Headquarter**	**Founded in**
Coinbase	40+	0.5	San Francisco, USA	2012
Binance	320+	0.1	Malta	2017
Okex	230	0.15	Malta	2017
BitMex	160+	0.075	Eden Island, Seychelles	2014
Bitfinex	30+	0.2	Hong Kong	2012
Huobi	310+	0.2	Seychelles	2013
KuCoin	270+	0.1	Mahe, Seychelles	2017
BitStamp	10+	0.5	Luxembourg	2011
Bitterx	320+	0.35	Seattle, US	2014
Kraken	60	0.26	San Francisco, USA	2011

Source - Amirzadeh et al. (2022)

The term “Artificial Intelligence (AI)” was used for the first time in a summer project in 1956 at Dartmouth College (McCarthy et al., 2006). Originally, it was a research discipline to develop a simulation machine for any feature of intelligence or learning in principle (Dick, 2019). There is still lack of a definition of AI which is widely accepted. However, AI is generally defined as the system which uses computers to make decisions and solve problems by imitating the ability and behaviour of human brain. AI encourages machines to exhibit the behaviours of humans like self-driving a car, accomplishing dangerous tasks, and boosting corporate productivity (Bughin et al., 2017).

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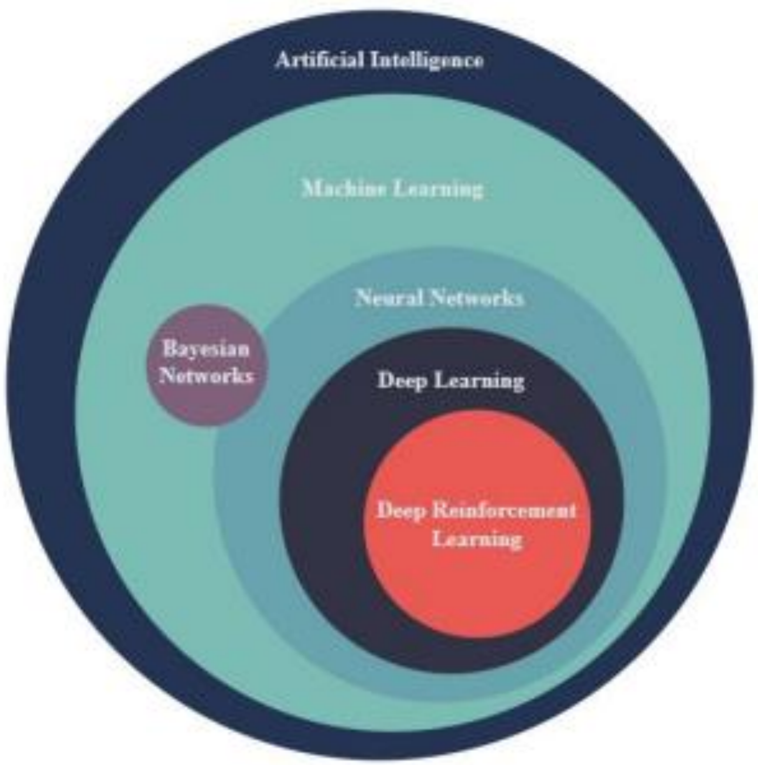
A lot of tech companies still give priority to AI over various IT projects irrespective of having various winters as a metaphor when businesses, technology, and media didn't pay much attention to AI (Floridi, 2020). As a result, AI is widely implemented in several domains, be it criminal justice, health, welfare and video streaming suggestions based on watch history or real-time analysis of big data and detecting fraud (Whittaker et al., 2018; Helm et al., 2020). AI and machine learning models are categorized frequently in a framework in which machine learning is considered as a subset of AI. Hence, a plausible categorization has been adopted to explain the models for predicting cryptocurrency prices (Janiesch et al., 2021; Zhang et al., 2021) (Figure 4).

Figure 4 – Categorization of AI and its subcategories



Source - Amirzadeh et al. (2022)

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Mathematicians, data scientists, computer scientists, and statisticians have developed and refined several machine learning models to gather vital knowledge from information available to come up with trustworthy and accurate movement and price predictors for performing profitable cryptocurrency trading. There are several factors affecting portfolio performance in financial markets like data granularity, quality of input data, forecasting models, and market maturity (Pang et al., 2020). Linear regression is very popular to approximate real-world models and have been most common over the years. There have been a lot of non-linear components in real-world and these approaches couldn't fit complicated datasets where other models are supposed to be very effective. A "multivariate linear regression" model has been implemented for prediction of prices of 10 cryptocurrencies by Mittal et al. (2018). High price is forecasted as per close price, open price, and low price of earlier days. Poongodi et al. (2020) combined Support Vector Machine (SVM) and Linear Regression" models to predict Ethereum prices. SVM achieved 10x higher accuracy without extra features than linear regression.

4.2. Supervised and Reinforcement Learning Models and their Applications in Cryptocurrency Market

Machine learning models have been helpful to investigate various functions and features of cryptocurrencies. Four machine learning models have been applied by Chowdhury et al. (2020) to predict close price of 9 cryptocurrencies. By comparing models, it is found that "K-nearest neighbour (K-NN)" showed poor performance.

4.1.1. Reinforcement Learning

AI is initially aimed to come up with completely autonomous agent that can work with the environment to learn ideal behaviours to improve over time with a specific goal (Arulkumaran et al., 2017). To achieve this objective, reinforcement learning agent follows a procedure to interact with an environment. The agent in every step is in state space and chooses action from action space. The agent goes through a policy for all these procedures of "state-action-state" and gets a scaler reward (Li, 2017). This configuration makes reinforcement learning especially effective to achieve the objective of AI. Figure 5 illustrates a framework for interactions of agent environment.

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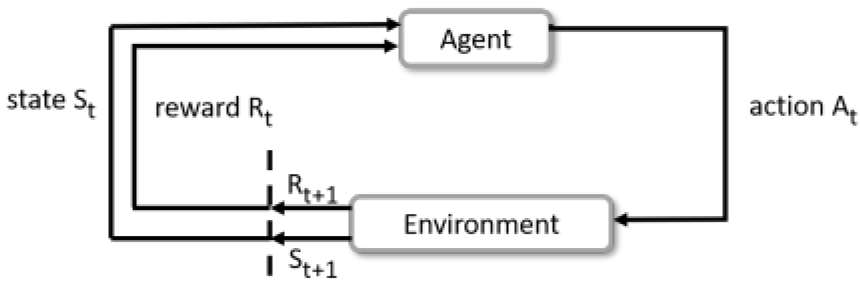
This way, an agent t is in a state S_t selects an action A_t and gets reward R_t. This action places agent to S_{t+1}. All such actions, rewards, and states are defined within the environment.

Figure 5 – Traditional Reinforcement Learning Cycle



Source - Amirzadeh et al. (2022)

Reinforcement learning goes through a specific paradigm as compared to unsupervised and supervised learning. It is basically an honourable mathematical model of "experience-based autonomous learning" (Sutton & Barto, 1998). It is not possible to classify reinforcement learning as a supervised learning method as labelled information is not given to the agent. In addition, RL approaches are ideal for issues with "sequential dynamics" and optimizes the goal of scaler performance, while "supervised learning" approaches are applicable to issues which consist of static input-output mappings" and reduce the mismatch among the model and data (Rosenstein et al., 2004).

4.1.2. Supervised Learning

Machine learning is an umbrella term as a subset of AI for algorithms and approaches for machines to find patterns without explicit guidelines for programming (Rasekhschaffe & Jones, 2019). Machine learning approaches conduct "experiential learning" related to "human intelligence" and improve analyses with algorithms (Helm et al., 2020). Various machine learning models learn from information in various ways like semi-supervised, supervised, unsupervised, and reinforcement learning. Supervised learning uses labelled information to train models for classification or prediction. Meanwhile, unsupervised learning is aimed to organize datasets in similar clusters or

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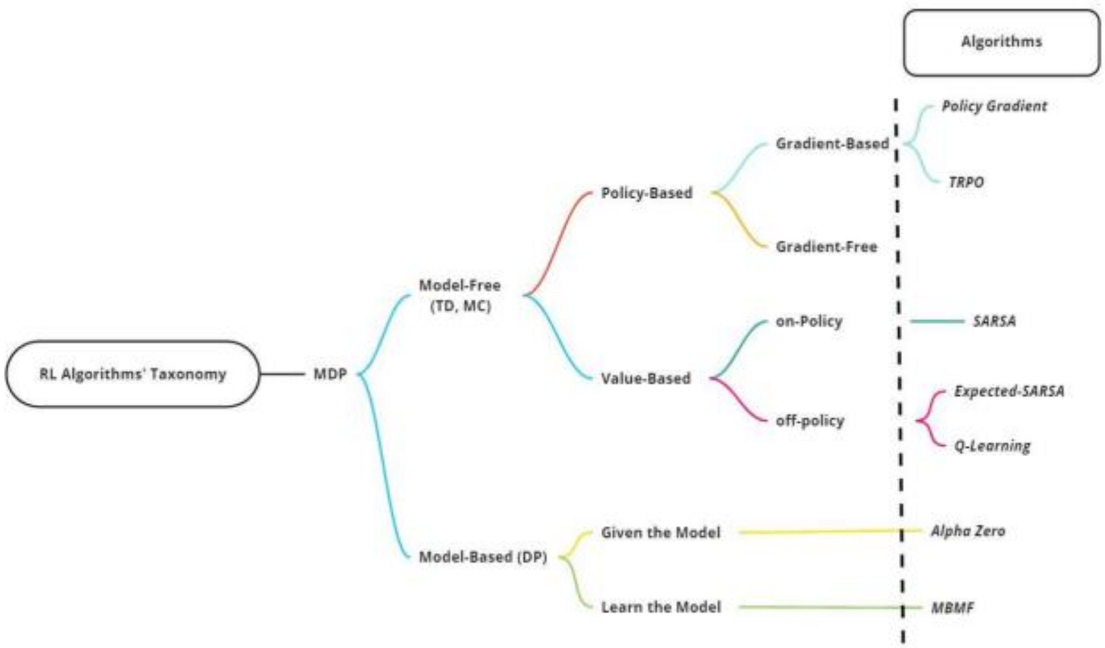
groups. There are no labels related to data points in "unsupervised learning" approaches. There are just partly labelled data which make semi-supervised learning, which combines supervised and unsupervised learning. Reinforcement learning models rely on action on the basis of rewards received to deal with environment and previous actions. Figure 6 illustrates a common taxonomy of reinforcement learning models which are produced as per Zhang & Yu (2020).

Figure 6 – Taxonomy of Reinforcement Learning Models



Source - Zhang & Yu (2020)

5. Results

As given in discussion, studies related to AI have been rising in cryptocurrency markets, especially in recent years. However, various unexplored topics still need further investigations with all scientific and technological advancements. Recent changes in crypto markets show that they are significantly combined with other conventional economic and financial systems. For example, Coinbase is one of the most common "cryptocurrency exchanges" which went popular on

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"NASDAQ exchange" and there is also a rise in ways where cryptocurrencies can be helpful to pay for products and services. This evidence shows acceptance of cryptocurrencies by current financial institutions and common public. With the evolution of economic and financial systems constantly, it becomes important to investigate the integration of cryptocurrency in financial assets.

Studies conducted on behavioral finance focus on the emotions of investors and their impact on financial decisions significantly. A lot of researchers have focused on "investor sentiment" with their social media activities (Sun et al., 2018). There are various unsupervised and supervised machine learning studies combining sentiment indicators with some of the financial aspects. However, studies related to reinforcement learning focus mainly on "sentiment analysis" as an individual input for prediction of prices. So, it is worth investigating sentimental factors and other financial inputs. Figure 7 illustrates volatility of Bitcoin prices as an example of effect of social influencers and sentiments because of two events of comments made by Elon Musk on Bitcoin. It is evident that large red candlesticks (price decline) and large green candlesticks (price rise) are the results of negative and positive tweets by Elon Musk, respectively, because of the impact accepted by traders. Several significant geopolitical events and emotional impact they create are used to extract similar diagrams.

Figure 7 – A Chart of Decline and Rise of Bitcoin Prices due to negative and positive comments by Elon Musk

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Source - Amirzadeh et al. (2022)

As the first cryptocurrency, Bitcoin is referenced and studied more than any other cryptocurrency. For instance, Bitcoin (blue) and altcoins (green) are compared from 2010 to 2019 in Google Books Ngram (Figure 8). The red curve indicates appearances of term "cryptocurrencies" in "Google Books Ngram viewer" for better context to compare. Bitcoin has been affected widely as compared to Altcoins. It shows the areas which are still unexplored about altcoins. With improved features, altcoins can be ideal to diversify portfolios and reduce overall investment risk (Nguyen et al, 2019).

Figure 8 – Comparison between Bitcoin and Altcoin in Google Books Ngram viewer

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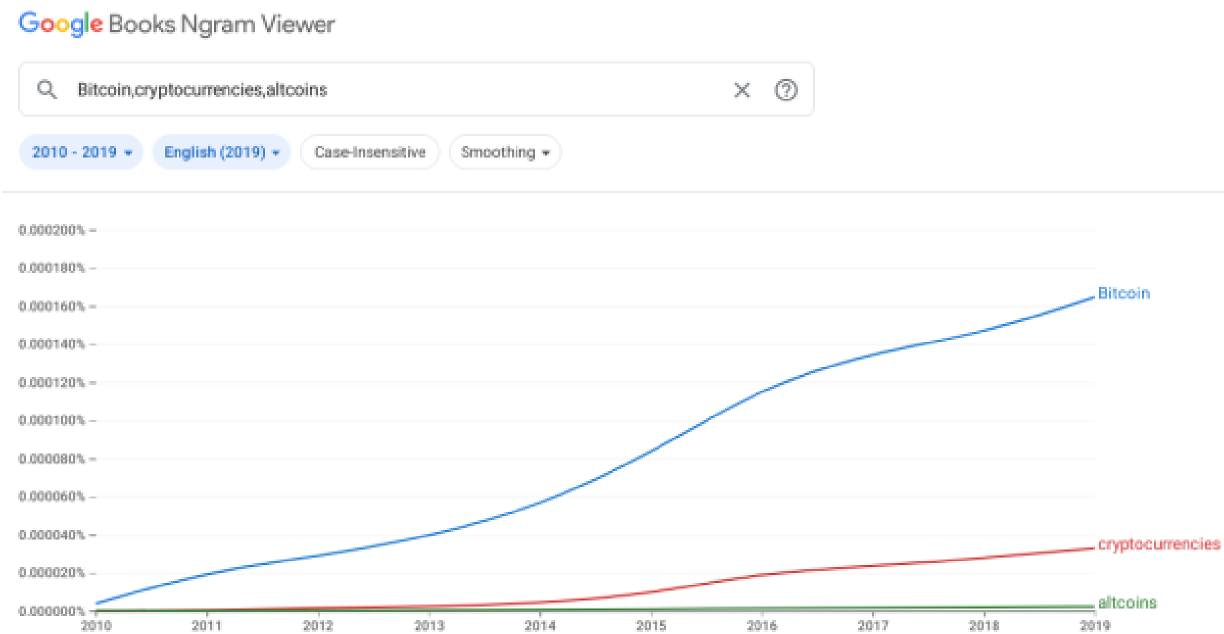

Source - Nguyen et al. (2019)

6. Conclusion

Cryptocurrency is quite a new field in economies and finance. There are plenty of open issues which still need further studies and use of modern AI approaches to predict cryptocurrency prices accurately. Further attention is required with special emphasis on integration of cryptocurrencies while analysing 2-way impact of causal and correlation relations and traditional markets. At the same time, AI can address these open challenges and future studies must include various tools and subsets to deal with aspects of data engineering to predict cryptocurrency prices. This study acts as a guiding light to future researchers to discuss open challenges. AI's potential can be clearly seen in cryptocurrency market and this research can help reap benefits for participants, decision-makers, and policymakers in cryptocurrency market.

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References

Trading View (2022). Crypto and DeFi market cap charts. Available at https://www.tradingview.com/markets/cryptocurrencies/global-charts/.

Ciaian, P., Rajcaniova, M., & Kancs, D. A. (2016). The economics of BitCoin price formation. *Applied economics, 48*(19), 1799-1815.

Ji, Q., Bouri, E., Gupta, R., & Roubaud, D. (2018). Network causality structures among Bitcoin and other financial assets: A directed acyclic graph approach. *The Quarterly Review of Economics and Finance*, *70*, 203-213.

Abraham, J., Higdon, D., Nelson, J., & Ibarra, J. (2018). Cryptocurrency price prediction using tweet volumes and sentiment analysis. *SMU Data Science Review*, *1*(3), 1.

Mittal, R., Arora, S., & Bhatia, M. P. S. (2018). Automated cryptocurrencies prices prediction using machine learning. *Division of Computer Engineering, Netaji Subhas Institute of Technology, India*, *8*, 2229-6956.

Wu, X., Chen, H., Wang, J., Troiano, L., Loia, V., & Fujita, H. (2020). Adaptive stock trading strategies with deep reinforcement learning methods. *Information Sciences*, *538*, 142-158.

Dai, S., Wu, X., Pei, M., & Du, Z. (2017). Big data framework for quantitative trading system. *Journal of Shanghai Jiaotong University (Science)*, *22*, 193-197.

Huang, B., Huan, Y., Xu, L. D., Zheng, L., & Zou, Z. (2019). Automated trading systems statistical and machine learning methods and hardware implementation: a survey. *Enterprise Information Systems*, *13*(1), 132-144.

Rasekhschaffe, K. C., & Jones, R. C. (2019). Machine learning for stock selection. *Financial Analysts Journal*, *75*(3), 70-88.

Chuen, D. L. K., & Deng, R. H. (2017). *Handbook of blockchain, digital finance, and inclusion: cryptocurrency, fintech, insurtech, regulation, Chinatech, mobile security, and distributed ledger*. Academic Press.

International Journal of Mechanical Engineering Research and Technology
ISSN 2454 – 5X

http://www.ijmert.com
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Leong, K., & Sung, A. (2018). FinTech (Financial Technology): What is it and how to use technologies to create business value in fintech way?. *International Journal of Innovation, Management and Technology*, *9*(2), 74-78.

Stulz, R. M. (2019). Fintech, bigtech, and the future of banks. *Journal of Applied Corporate Finance*, *31*(4), 86-97.

Mosavi, A., Faghan, Y., Ghamisi, P., Duan, P., Ardabili, S. F., Salwana, E., & Band, S. S. (2020). Comprehensive review of deep reinforcement learning methods and applications in economics. *Mathematics*, *8*(10), 1640.

Sabry, F., Labda, W., Erbad, A., & Malluhi, Q. (2020). Cryptocurrencies and artificial intelligence: Challenges and opportunities. *IEEE Access*, *8*, 175840-175858.

Ozbayoglu, A. M., Gudelek, M. U., & Sezer, O. B. (2020). Deep learning for financial applications: A survey. *Applied Soft Computing*, *93*, 106384.

Amirzadeh, R., Nazari, A., & Thiruvady, D. (2022). Applying Artificial Intelligence in Cryptocurrency Markets: A Survey. *Algorithms*, *15*(11), 428.

Strobel, V. (2018). Pold87/academic-keyword-occurrence: First release. *DOI*, *10*, 5281.

Fang, F., Ventre, C., Basios, M., Kanthan, L., Martinez-Rego, D., Wu, F., & Li, L. (2022). Cryptocurrency trading: a comprehensive survey. *Financial Innovation*, *8*(1), 1-59.

Sahu, S. K., Mokhade, A., & Bokde, N. D. (2023). An Overview of Machine Learning, Deep Learning, and Reinforcement Learning-Based Techniques in Quantitative Finance: Recent Progress and Challenges. *Applied Sciences*, *13*(3), 1956.

Mujlid, H. (2023, March). A Survey on Machine Learning Approaches in Cryptocurrency: Challenges and Opportunities. In *2023 4th International Conference on Computing, Mathematics and Engineering Technologies (iCoMET)* (pp. 1-6). IEEE.

Awotunde, J. B., Ogundokun, R. O., Jimoh, R. G., Misra, S., & Aro, T. O. (2021). Machine learning algorithm for cryptocurrencies price prediction. In *Artificial Intelligence for Cyber Security: Methods, Issues and Possible Horizons or Opportunities* (pp. 421-447). Cham: Springer International Publishing.

International Journal of Mechanical Engineering Research and Technology
ISSN 2454 – 5X

http://www.ijmert.com
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Jiang, W. (2021). Applications of deep learning in stock market prediction: recent progress. *Expert Systems with Applications*, *184*, 115537.

Felizardo, L. K., Paiva, F. C. L., de Vita Graves, C., Matsumoto, E. Y., Costa, A. H. R., Del-Moral-Hernandez, E., & Brandimarte, P. (2022). Outperforming algorithmic trading reinforcement learning systems: A supervised approach to the cryptocurrency market. *Expert Systems with Applications*, *202*, 117259.

Al-Jaroodi, J., & Mohamed, N. (2019). Blockchain in industries: A survey. *IEEE Access*, *7*, 36500-36515.

Lansky, J. (2018). Possible state approaches to cryptocurrencies. *Journal of Systems integration*, *9*(1), 19.

European Central Bank (2012). *Virtual Currency Schemes*. EC Bank, Virtual Currency Schemes (h. 13–14). European Central Bank: Frankfurt, Germany, 2012.

Amirzadeh, R., Nazari, A., & Thiruvady, D. (2022). Applying Artificial Intelligence in Cryptocurrency Markets: A Survey. *Algorithms*, *15*(11), 428.

Patel, M. M., Tanwar, S., Gupta, R., & Kumar, N. (2020). A deep learning-based cryptocurrency price prediction scheme for financial institutions. *Journal of information security and applications*, *55*, 102583.

McCarthy, J., Minsky, M. L., Rochester, N., & Shannon, C. E. (2006). A proposal for the dartmouth summer research project on artificial intelligence, august 31, 1955. *AI magazine*, *27*(4), 12-12.

Dick, S. (2019). Artificial Intelligence. HDSR. Available online: https://hdsr.duqduq.org/pub/0aytgrau.

Bughin, J., Hazan, E., Ramaswamy, S., Chui, M., Allas, T., Dahlstrom, P., ... & Trench, M. (2017). Artificial intelligence: the next digital frontier?.

Floridi, L. (2020). AI and its new winter: From myths to realities. *Philosophy & Technology*, *33*, 1-3.

International Journal of Mechanical Engineering Research and Technology
ISSN 2454 – 5X
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Vol. 16 Issue 1, March 2024

Whittaker, M., Crawford, K., Dobbe, R., Fried, G., Kaziunas, E., Mathur, V., ... & Schwartz, O. (2018). *AI now report 2018* (pp. 1-62). New York: AI Now Institute at New York University.

Helm, J. M., Swiergosz, A. M., Haeberle, H. S., Karnuta, J. M., Schaffer, J. L., Krebs, V. E., ... & Ramkumar, P. N. (2020). Machine learning and artificial intelligence: definitions, applications, and future directions. *Current reviews in musculoskeletal medicine*, *13*, 69-76.

Janiesch, C., Zschech, P., & Heinrich, K. (2021). Machine learning and deep learning. *Electronic Markets*, *31*(3), 685-695.

Zhang, W., Li, H., Li, Y., Liu, H., Chen, Y., & Ding, X. (2021). Application of deep learning algorithms in geotechnical engineering: a short critical review. *Artificial Intelligence Review*, 1-41.

Pang, X., Zhou, Y., Wang, P., Lin, W., & Chang, V. (2020). An innovative neural network approach for stock market prediction. *The Journal of Supercomputing*, *76*, 2098-2118.

Poongodi, M., Sharma, A., Vijayakumar, V., Bhardwaj, V., Sharma, A. P., Iqbal, R., & Kumar, R. (2020). Prediction of the price of Ethereum blockchain cryptocurrency in an industrial finance system. *Computers & Electrical Engineering*, *81*, 106527.

Chowdhury, R., Rahman, M. A., Rahman, M. S., & Mahdy, M. R. C. (2020). An approach to predict and forecast the price of constituents and index of cryptocurrency using machine learning. *Physica A: Statistical Mechanics and its Applications*, *551*, 124569.

Arulkumaran, K., Deisenroth, M. P., Brundage, M., & Bharath, A. A. (2017). Deep reinforcement learning: A brief survey. *IEEE Signal Processing Magazine*, *34*(6), 26-38.

Li, Y. (2017). Deep reinforcement learning: An overview. *arXiv preprint arXiv:1701.07274*.

Sutton, R. S., & Barto, A. G. (1998). Introduction to reinforcement learning. MIT Press. *Cambridge, MA.*

Rosenstein, M. T., Barto, A. G., Si, J., Barto, A., Powell, W., & Wunsch, D. (2004). Supervised actor-critic reinforcement learning. *Learning and Approximate Dynamic Programming: Scaling Up to the Real World*, 359-380.

International Journal of Mechanical Engineering Research and Technology
ISSN 2454 – 5X

http://www.ijmert.com
Vol. 16 Issue 1, March 2024

Helm, J. M., Swiergosz, A. M., Haeberle, H. S., Karnuta, J. M., Schaffer, J. L., Krebs, V. E., ... & Ramkumar, P. N. (2020). Machine learning and artificial intelligence: definitions, applications, and future directions. *Current reviews in musculoskeletal medicine*, *13*, 69-76.

Zhang, H., & Yu, T. (2020). Taxonomy of reinforcement learning algorithms. *Deep Reinforcement Learning: Fundamentals, Research and Applications*, 125-133.

Sun, Y., Fang, M., & Wang, X. (2018). A novel stock recommendation system using Guba sentiment analysis. *Personal and Ubiquitous Computing*, *22*, 575-587.

Nguyen, T. V. H., Nguyen, B. T., Nguyen, T. C., & Nguyen, Q. Q. (2019). Bitcoin return: Impacts from the introduction of new altcoins. *Research in International Business and Finance*, *48*, 420-425.