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A Comprehensive Survey of Cryptocurrency Forecasting: Methods, Trends, and Challenges

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ABSTRACT

This comprehensive survey paper explores the diverse landscape of cryptocurrency forecasting, tracing its evolution from an alternative to traditional monetary systems to its significant growth in the global financial arena. It consolidates existing research by categorizing and analyzing 234 scholarly articles, organizing them into machine learning, deep learning, deep reinforcement learning, and statistical methodologies, and evaluating the related metrics. The case study titled "Examining the performance differences between backtesting and forward testing" highlights the challenges investors face, as strategies that appear effective in backtesting often fail in practical use. Another case study, "Social Data Exploration in Cryptocurrency Trends," examines how social media data can provide insights into market movements and investor sentiment, revealing the impact of social trends on cryptocurrency prices. The findings section provides a detailed view, illuminating trends such as yearly publication rates, methodological distributions, input features, training/testing splits, the total number of data samples considered, and forecasting time horizons. This survey paper serves as a valuable resource, providing researchers and investors with a solid foundation for understanding and navigating the dynamic field of cryptocurrency forecasting.

I. PENDAHULUAN

In human history, currency systems have always played a vital role in shaping economies, societies, and the global financial landscape. The evolution of currency systems has been continuous, progressing from ancient barter systems to modern central banks and fiat currencies [1]. Traditional monetary systems are predominantly based on fiat currencies, characterized by government and central bank control over the issuance and regulation of money. However, this system faces several challenges, including inflation risk, dependence on intermediaries like banks, and centralization. Moreover, traditional currencies may not be accessible to unbanked individuals, limiting their ability to save money, make investments, or engage in financial activities. This exclusion underscores the importance of exploring alternative economic systems to address these limitations.

Digital currencies can be traced in 2008 when an anonymous figure using the pseudonym Satoshi Nakamoto published a groundbreaking whitepaper "Bitcoin: A Peer-to-Peer Electronic Cash Sys- tem" [2]. This whitepaper introduced a decentralized digital currency system that operates independently of traditional financial intermediaries. The year 2009 marked the birth of the first cryptocurrency Bitcoin. Bitcoin was built upon blockchain technology which revolutionized the concept of trust by relying on cryptographic proofs rather than centralized authorities. Anyone can facilitate direct peer-to-peer transactions on a blockchain network without any processing times.

The cryptocurrency market experienced a significant surge in December 2017 [3], marked by Bitcoin's price skyrocketing to nearly $20,000, garnering global attention. This period also witnessed the emergence of numerous alternative cryptocurrencies alongside Bitcoin. Among these, Ether stands out as a notable creation introduced by Vitalik Buterin and his team in July 2015 [4].

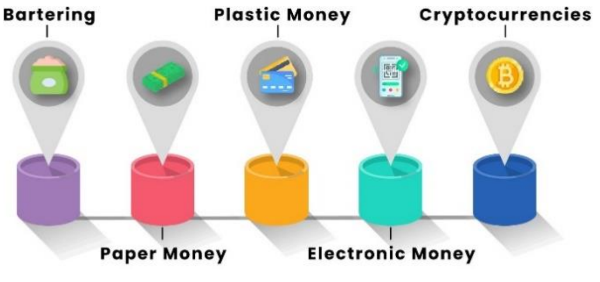

Figure 1. From bartering shells to digital wallets: the journey of currency evolution in one glance

The cryptocurrency boom created new exciting opportunities for investors due to its high market volatility. This volatility is due to multiple factors like speculative trading regulatory developments market sentiment and macroeconomic events. Therefore 24 hour trading environments cause market volatility as compared to traditional financial markets.

This survey paper holds significant importance within the realm of cryptocurrency research and market analysis. It undertook a comprehensive examination of 234 scholarly articles about cryptocurrency forecasting. Given the inherent volatility of the cryptocurrency market this survey offers a thorough exploration and data driven analysis of recent research endeavors. By synthesizing a wide array of literature this survey paper aims to furnish a comprehensive overview of prevailing trends methodologies and challenges in the domain of cryptocurrency forecasting.

Existing surveys often focus narrowly on specific cryptocurrencies. Olvera et al. [5] conducted a study exclusively on Bitcoin price forecasting primarily relying on hybrid models such as ARIMA. Fang et al. [6] undertook an extensive analysis of research papers covering various aspects of cryptocurrency trading systems and extreme market conditions. Sina et al. [7] focused on forecasting cryptocurrency market volatility albeit with a narrow emphasis on Artificial Neural Networks. Abubakar et al. [8] provided a survey specifically targeting the forecasting of digital assets using Machine Learning based technologies from 2014 to 2022.

Our survey article covers a wide range of forecasting models including Machine Learning Deep Learning Deep Reinforcement Learning and Statistical Models. By exploring these different methodologies this study offers readers a holistic understanding of the diverse approaches used in cryptocurrency forecasting. In addition to reviewing existing literature this survey includes insightful case studies and analyses of social data. This survey investigates the performance disparities between back testing and forward testing methodologies shedding light on the challenges and limitations faced by forecasters in practical settings.

In this survey paper an exploration unfolds across key artificial intelligence paradigms. Machine Learning is a diverse field with a variety of algorithms that serve as powerful tools in cryptocurrency forecasting including Support Vector Machines Support Vector Regression Random Forest Linear Regression Naive Bayes and K Nearest Neighbors. Deep Learning incorporates Artificial Neural Networks Convolutional Neural Networks Recurrent Neural Networks Long Short Term Memory and Gated Recurrent Units. Deep Reinforcement Learning brings a level of sophistication by combining neural networks with reinforcement learning principles utilizing algorithms like Proximal Policy Optimization Advantage Actor Critic and Deep Q Network. Statistical models such as Autoregressive integrated moving average and Generalized Autoregressive Conditional Heteroskedasticity models have a rich history in financial forecasting excelling at capturing short term trends patterns and volatility based on historical price data.

II. Method

The research methodology for this study is bifurcated into two primary components a systematic literature review and empirical case study evaluations.

For the systematic literature review a comprehensive examination of 234 scholarly articles about cryptocurrency forecasting was undertaken. The selection process was driven by the collective wisdom of the research community analyzing publications spanning the last decade. Articles were categorized into four distinct learning paradigms Machine Learning Deep Learning Deep Reinforcement Learning and Statistical Models. Within these paradigms data was meticulously extracted regarding the forecasting time horizons evaluation metrics input features currency types and the distribution of data samples used for training and testing splits. To address the performance gap often observed between theoretical models and live market application an empirical case study approach was utilized. The methodology involved data collection tailored to accommodate the unique input requirements of each forecasting algorithm. The study harnessed the 24 hour price data for Bitcoin sourced from BitMEX. The dataset was partitioned into distinct temporal

phases.

The training data spanned from January 1 2017 to July 1 2022. This extended period was chosen for its substantial coverage of market conditions encompassing various pivotal events bull and bear markets and macroeconomic shifts allowing the algorithms to capture diverse market dynamics. The back testing data spanned from July 1 2022 to July 1 2023 designed to simulate the performance of the forecasting models on historical data following the training period. Finally the forward testing data spanned from July 1 2023 to January

1 2024 to assess the performance of the algorithms in a real world out of sample scenario simulating live market conditions.

Data preprocessing involved feature engineering to craft elements specific to the forecasting algorithms. For sequential models like Long Short Term Memory and Transformers sequential data enriched with lag features was generated to capture temporal dependencies. For statistical models like ARIMA time series differencing was applied to achieve stationarity. Scaling and standardization were applied for variance sensitive algorithms such as Support Vector Machines. The algorithms were evaluated primarily using Cumulative Profit and Loss which encapsulates the total profit or loss generated reflecting the model effectiveness in real world trading conditions where sustained profitability is the key consideration.

Furthermore social data exploration was conducted by analyzing Google Trends search volumes Reddit comment frequencies and cryptocurrency news article counts comparing their temporal spikes with corresponding Bitcoin price movements to establish sentiment correlation.

III. Results And Discussion

A. Overall Publication and Methodological Trends

In this segment of the study this survey delves into the annual publication trends within the realm of researched papers. As illustrated in Figure 2 the survey provides a visual representation of the yearly publication patterns. This pie chart vividly portrays the changing landscape signifying a growing interest in this domain expressing the annual distribution of published papers in percentage terms. Notably there was a significant upswing in research papers related to cryptocurrency forecasting in 2022 and 2023.

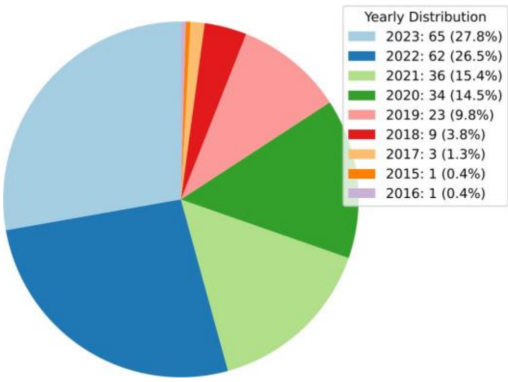

Figure 2. Pie chart illustrates the proportion of published papers in percentage terms across different years within the scope of the survey conducted in 2023.

The survey conducts a detailed analysis of overall methodologies employed within the study corpus. Figure 3 presents a detailed pie chart visualization depicting the distribution of learner types. This visual representation enriches the understanding of the specific procedures adopted across the cryptocurrency forecasting research landscape. Deep Learning algorithms constitute the largest slice of the pie followed by Machine Learning and Statistical Models.

An in depth analysis of the overall time horizons considered in the researched papers reveals a notable trend. Figure 4 complements this analysis with a pie chart representing the percentage wise distribution of time horizons. The pie chart highlights that over 67 percent of the published research papers focused on the 24 hour time horizon. The second largest segment is the 1 hour time horizon.

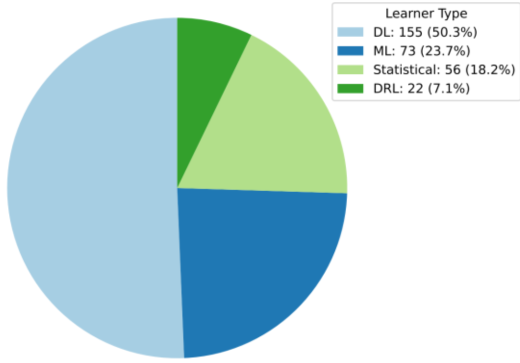

Figure 3. Pie chart illustrates the distribution of learner types among surveyed research papers in cryptocurrency forecasting.

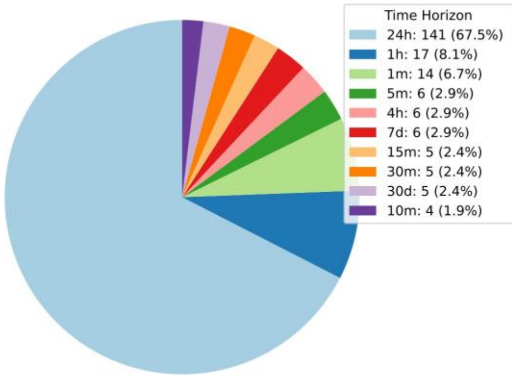

Figure 4. Pie chart illustrates the percentage wise distribution of time horizons across cryptocurrency forecasting research papers.

The pie chart in Figure 5 clearly illustrates the distribution of evaluation metrics used across a range of cryptocurrency forecasting research studies. Notably the preeminent segment is occupied by the Root Mean Square Error. This stands as a cornerstone metric in evaluating the predictive accuracy of forecasting models followed closely by Mean Absolute Error providing insights into the average magnitude of errors present in forecasts.

Figure 6 provides a percentage wise distribution of input feature categories across the research papers. The pie chart reveals that the majority of the input features fall under the price data category signifying its widespread usage as a primary input. Following closely sentimental data emerges as the second largest segment suggesting its considerable importance in shaping forecasting models.

In Figure 7 a graphical representation of the percentage wise distribution of research papers across various cryptocurrencies is provided. Each slice of the pie corresponds to a specific digital currency. Bitcoin commands the largest portion of the pie constituting approximately 46 percent of the research papers. Ether claims the second largest slice describing a significant portion of the research landscape.

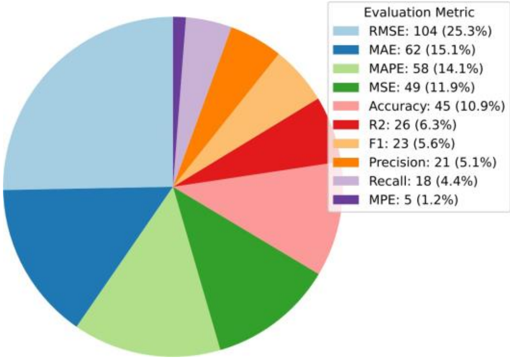

Figure 5. Pie chart depicts the percentage wise distribution of evaluation metrics utilized in cryptocurrency forecasting research papers.

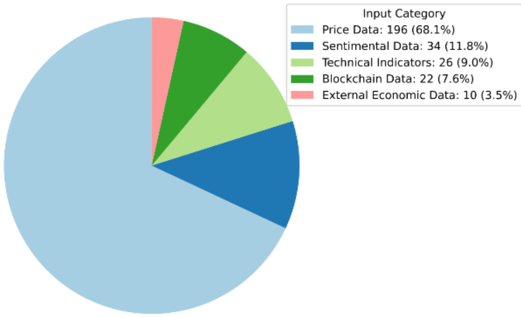

Figure 6. Pie chart illustrates the percentage wise distribution of input feature categories in cryptocurrency forecasting research papers.

B. *Machine Learning Approaches in Forecasting*

Cryptocurrency markets are known for their volatility and complexity making accurate forecasting a challenging task. Researchers have turned to Machine Learning techniques to analyze historical data and predict future price movements. Figure 8 illustrates a pie chart representation demonstrating the prevalence of various Machine Learning techniques utilized in recent research papers. Linear Regression has been prominently featured closely followed by Random Forest Support Vector Machines and K Nearest Neighbors. Examining the currency wise distribution within Machine Learning literature provides valuable insights. Figure 9 illustrates the proportional representation via a pie chart. Bitcoin emerges as the dominant cryptocurrency followed by Ether Ripple and Litecoin.

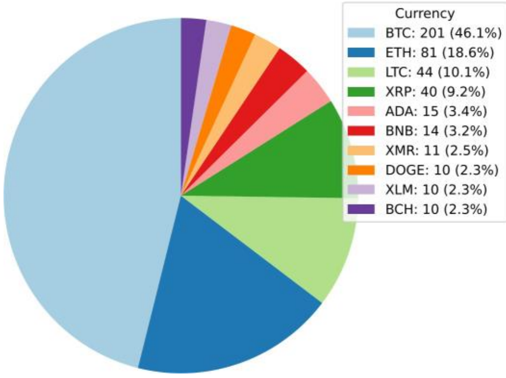

Figure 7. Pie chart visually depicts the percentage wise distribution of research papers across various cryptocurrencies.

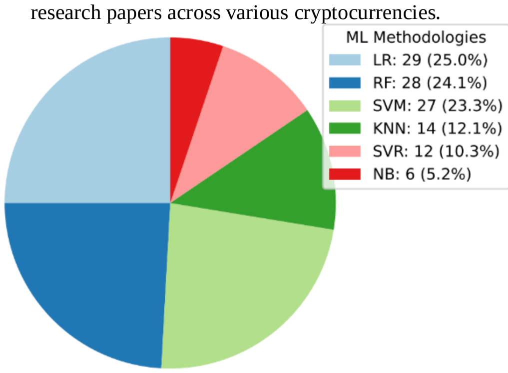

Figure 8. Pie chart representing methodological distribution in Machine Learning literature.

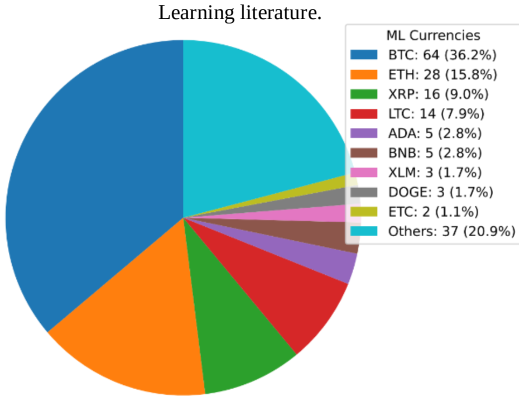

Figure 9. Pie chart of currency wise distribution in Machine Learning literature.

An examination of the time horizon wise distribution within Machine Learning literature via a pie chart in Figure 10 reveals that the 24 hour time horizon dominates the distribution.

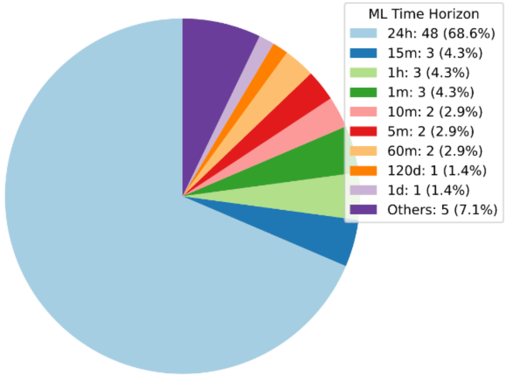

Figure 10. Pie chart of time horizon wise distribution in Machine Learning literature.

In the realm of cryptocurrency forecasting a consistent thread weaves through several notable studies. Nor et al. [9] laid a sturdy foundation in 2018 by embarking on an extensive exploration encompassing seven major cryptocurrencies. Leveraging Support Vector Machines they examined daily trading data to predict price movements within a 24 hour horizon. Their classifier displayed exceptional performance boasting a remarkable accuracy rate. Shifting focus exclusively to Bitcoin Majid et al. [10] embraced both Statistical and Deep Learning methodologies harnessing Support Vector Machines Random Forest and DL models within the familiar 24 hour prediction window. It is noteworthy that the Random Forest model distinguished itself by yielding the smallest root mean square error within their dataset.

Building upon these insights Franco et al. [11] ventured into cryptocurrency forecasting echoing a 24 hour prediction window introducing a unique twist by incorporating sentiment data alongside price data for Bitcoin Ether Ripple and Litecoin. While SVM and Random Forest excelled with price data an intriguing revelation emerged the Multi Layer Perceptron model asserted itself as the top performer. Support vector machines have been a prominent option among researchers. Ismail et al. [9] utilized SVM on price data achieving forecasts with Mean Absolute Percentage Error metrics. Cohen et al. [12] applied Support Vector Machines to cryptocurrency price forecasting with a 24 hour time horizon. Alahmari et al. [13] applied Support Vector Regression for BTC XRP and ETH price predictions evaluating with mean absolute error mean squared error and R squared.

Hakan et al. [14] conducted a study centered on Bitcoin incorporating price data technical indicators and various classifiers including Support Vector Machines and Random

Forests assessing model performance using metrics like Accuracy Mean Absolute Error and Root Mean Square Error. Khedmati et al. [15] focused their study on Bitcoin utilizing closing price data and Statistical models to predict price movements within a 24 hour time horizon. In the year 2020 Saad et al. [13] included Bitcoin Ripple and Ether in their study exclusively utilizing Support Vector Regression by integrating price data with external economic indicators evaluated using metrics like Mean Absolute Error and Mean Squared Error.

In a unique departure from conventional methodologies Alireza et al. [16] introduced sentimental data as input features exclusively for Bitcoin forecasting achieving impressive accuracy. Lokesh et al. [17] conducted a cryptocurrency forecasting study concentrating on Bitcoin encompassing Linear Regression and DL algorithms with a 24 hour time horizon. In 2020 Vidyulatha et al. [18] undertook a comprehensive study focusing on Bitcoin incorporating historical price data and applying Linear Regression in conjunction with Statistical Models extending the time horizon to 120 days revealing the superior performance of Statistical models in comparison to the LR model.

In 2021 Patrick et al. [19] conducted a focused study on Bitcoin price prediction. They used a wide range of input features including technical indicators blockchain data and sentimental data applying Machine Learning models such as Random Forest Gradient Boosting Classifiers Logistic Regression and Deep Learning models. The findings revealed that Recurrent Neural Networks and Gradient Boosting Classifiers consistently provided more accurate predictions. In 2021 Mohamed et al. [20] conducted a prediction study focusing on multiple cryptocurrencies employing price data and utilizing Support Vector Machines in conjunction with other Deep Learning models introducing an enhanced Scatter Search Algorithm approach to optimize SVM.

In 2021 Erdinc et al. [21] focused on cryptocurrency price prediction utilizing price data as input features and employed a range of Machine Learning models including SVM and other Deep Learning models with a time horizon of 24 hours proposing an enhanced SCA approach to optimize SVM. In 2021 Andrew et al. [22] conducted a forecasting study focusing on Bitcoin Ether and Ripple utilizing price data with a 24 hour time horizon employing Linear Regression Support Vector Machines k nearest Neighbors Decision Trees Random Forest AdaBoost and XGBoost finding that Support Vector Machines provided the most accurate classifications. In 2021 Ashutosh et al. [23] conducted a price prediction study incorporating price data as input features employing various regression models including Linear Regression Theil Sen Regression and Huber Regression. In a parallel effort Mudassir et al. [24] delved into cryptocurrency forecasting extending their analysis to various time horizons including 1 day 7 days 30 days and 90 days exclusively focusing on Bitcoin employing Support Vector Machines and Deep Learning models.

Martin Barreiro et al. [25] utilized Support Vector Machines for multi cryptocurrency price forecasting including Binance Coin Bitcoin Cardano Dogecoin Ether and Ripple with a 24 hour time horizon. Rena et al. [26] conducted multi currency forecasting considering Bitcoin Ether Ripple Cardano Dogecoin Polkadot and Litecoin involving Support Vector Machines for predictions with a 24 hour time horizon.

Valde´s Aguirre et al. [11] integrated price data and sentiment analysis using Support Vector Machines and Random Forest for forecasting BTC ETH XRP and LTC prices. Rabbania et al. [27] employed regression models including Linear Regression Gradient Boosting Regression Support Vector Regression and Random Forest Regression for BTC ETH ZEC and LTC price forecasting.

Pinellas et al. [28] explored Support Vector Regression Linear Regression K nearest neighbors and Decision Tree Regression for short term cryptocurrency forecasting. Azizi et al. [15] and Azizi et al. [10] explored Bayesian models alongside SVM and RF for BTC price prediction. Anbarasi et al. [29] adopted a straightforward Linear Regression model to predict cryptocurrency prices targeting both short term and long term forecasting. Amirhosseini et al. [30] integrated sentiment data with Machine Learning employing K Nearest Neighbors Logistic Regression Gaussian Naive Bayes Support Vector Machine and Extremely Randomized Trees models to predict BTC prices over a 24 hour horizon. Johari et al. [31] conducted research concentrating on AVAX XRP SOL DOGE MATIC and SHIB utilizing Linear Regression Stochastic Gradient Descent Regression and Random Forest Regression.

Godinho et al. [32] conducted multi currency forecasting considering BTC ETH and LTC including Linear Regression Random Forest and Support Vector Machine. Geetha et al. [33] explored an array of regression models for Bitcoin price prediction including Linear Regression Gradient Boosting Regression Random Forest Decision Trees Adaboost Regression Ridge Regression and Lasso Regression. Arpitha et al. [18] utilized Linear Regression to predict Bitcoin prices over a 120 day time horizon. Jatto et al. [34] focused on Bitcoin price forecasting using Support Vector Machines and K Nearest Neighbors models with a 24 hour time horizon. Bhat et al. [35] employed Linear Regression and Support Vector Regression for short term Bitcoin price forecasting with a 1 hour time horizon. Lee et al. [36] explored Bitcoin price prediction using various models including Bayesian Neural Networks Support Vector Regression and Support Vector Machines with a 24 hour time horizon.

Das et al. [37] investigated Bitcoin price forecasting using Adaptive Neuro Fuzzy Inference System Random Forest Support Vector Regression Multivariate Adaptive Regression Splines and Lasso Regression with a 24 hour time horizon. Bhosale et al. [38] explored classification models including Support Vector Machine Linear Regression K Means

Clustering Naive Bayes Random Forest K Nearest Neighbors and Decision Trees for Bitcoin price forecasting with a 1 minute time horizon. Qusef et al. [39] conducted multi currency forecasting encompassing Bitcoin Ether and Litecoin involving Support Vector Machines K nearest neighbors and Light Gradient Boosting Machines. Vijayakumar et al. [40] employed Linear Regression models for cryptocurrency forecasting covering Bitcoin Dash Litecoin Dogecoin Ether and Monero with a 24 hour time horizon. Neha et al. [35] cast an exclusive spotlight on Bitcoin meticulously examining price data within a 1 hour prediction horizon including Linear Regression and Support Vector Regression. Prakash et al. [17] utilized price data and blockchain data as input for models using the LR model for BTC with a 24 hour time horizon. Khasteh et al. [41] focused on Price Data for ETH LTC BTC and ZEC BTC with a 4 hour time horizon. Ioannis et al. [28] expanded their research to encompass BTC ETH and XRP employing a range of ML classifiers. Lekkala et al. [42] conducted a comprehensive study focused on Bitcoin price prediction over a 24 hour time horizon applying LASSO Decision Trees and K Nearest Neighbors. Tri et al. [43] concentrated on predicting cryptocurrency prices primarily Bitcoin using the Adaptive Neuro Fuzzy Inference System and Statistical models. Gessl et al. [44] incorporated RF on external economic price and blockchain data to predict BTC and LONA prices. Kaushik et al. [45] applied Random Forest for short term price forecasting of BTC. KP et al. [46] employed the Random Forest model for short term Bitcoin price forecasting with a 24 hour time horizon.

Ensemble learning methods have shown promise in cryptocurrency forecasting. Gyameraha et al. [47] explored cryptocurrency price forecasting particularly focusing on BTC utilizing Random Forest and Support Vector Regression. Lyu et al. [22] integrated multiple ensemble methods for forecasting BTC ETH and XRP prices emphasizing accuracy indicating that Support Vector Machine when utilized with a probability based trading strategy demonstrates high log returns. Zhang et al. [48] harnessed ensemble models including Logistic Regression SVM Random Forest XGBoost and LightGBM incorporating technical indicators for BTC price forecasting. Balci et al. [49] explored a comprehensive set of Machine Learning models including Support Vector Regression Decision Tree Regression Random Forest Regression Linear Regression Logistic Regression and Gaussian Process Regression to forecast major cryptocurrencies. Weinhardt et al. [50] introduced lagged data analysis with Logistic Regression Random Forest and Gradient Boosting Classifier for predicting cryptocurrency prices. Gregorio et al. [51] integrated external economic data into their models leveraging LR SVM and RF. Souza et al. [52] employed LightGBM XGBoost and LR models to predict BTC ETH BNB ADA and XRP prices. Ongan et al. [14] employed Support Vector Machines Naive Bayes Random Forest and Logistic Regression on BTC price data.

Uddin et al. [21] utilized KNN LR Naive Bayes RF SVM and Ensemble Gradient Boosting with various time intervals for BTC price forecasting. Kate et al. [53] applied KNN RF and Support Vector Regression to predict the prices of XRP BTC LTC ETH and XMR. Asgarim et al. [54] utilized a multi model ensemble approach for Bitcoin price prediction incorporating models such as Multilayer Perceptron Linear Regression Bayesian Ridge Regression Random Forest Regression Lasso Regression and Support Vector Regression. Time series forecasting employing Prophet and boosting models has emerged as a prevalent Machine Learning approach. Iqbal et al. [55] used Prophet and XG Boosting models for BTC price predictions focusing on RMSE Mean Absolute Error and R squared. Lim et al. [56] utilized the Prophet and XGBoost models for BTC ETH and XRP price forecasting. Han et al. [36] utilized gradient boosting models for cryptocurrency forecasting covering BTC ETH XRP BCH LTC DASH ETC and KRW with a time horizon of 10 minutes. Sunny et al. [57] examined Time Series models including Prophet alongside XGBoost for Bitcoin price forecasting. Dhawale et al. [58] focused on sentiment analysis for BTC using XGBoost models. Abbasib et al. [59] expanded their focus to BTC and utilized Random Forest XGBoost and LightGBM models. Zhang et al. [60] leveraged the Light Gradient Boosting Machine and XGBoost models for price predictions of BTC ETH BNB AVAX and SOL. Kolokotronis et al. [61] used the XGBoost model for Ether price prediction incorporating blockchain data and technical indicators. Khasteh et al. [41] conducted a study in cryptocurrency forecasting with a focus on multiple digital assets employing K Nearest Neighbors Extreme Gradient

Boosting and Random Forest with a 4 hour time horizon.

1) Deep Learning Approaches: Deep Learning has emerged as a powerful tool for cryptocurrency price prediction owing to its capability to capture intricate patterns and dependencies in data. In Figure 11 a pie chart examination of the distribution of methodologies specific to Deep Learning sheds light on prevalent trends. Long Short Term Memory networks emerge as the predominant methodology constituting over half of the pie chart followed by Gated Recurrent Unit architectures and Convolutional Neural Networks.

The currency wise distribution pie chart in Figure 12 provides valuable insights into the prevalence of various cryptocurrencies across deep learning research papers highlighting Bitcoin as the dominant cryptocurrency utilized. An examination of time horizon wise distribution via the pie chart in Figure 13 reveals that a significant majority of studies focus on a 24 hour time horizon.

In 2015 Joao et al. [62] embarked on a significant study dedicated to cryptocurrency forecasting with a specific focus on Bitcoin historical price harnessing the capabilities of an Artificial Neural Network as a predictive model for forecasting Bitcoin prices within a 24 hour time frame. In 2018 Nor et al. [9] and Brandon et al. [63] conducted research studies to predict the prices of various cryptocurrencies within a 24 hour time horizon utilizing price data as the primary input feature. In 2019 Franco et al. [11] conducted an insightful research study aimed at predicting the prices of various cryptocurrencies integrating both price data and sentimental data into their predictive model indicating that their proposed Deep Learning model outperformed the other methods. In 2019 Rini et al. [64] conducted a research study to predict Bitcoin prices within a narrow 1 hour time horizon incorporating price data and an Artificial Neural Network. In 2020 Hakan et al. [14] conducted a comprehensive research study to predict Bitcoin prices utilizing price data in conjunction with technical indicators deploying Artificial Neural Networks. In 2022 Jaehyun et al. [65] and Zubair et al. [66] conducted separate research studies with the common goal of predicting the prices of various cryptocurrencies over a 24 hour time horizon using price data and Deep Learning based models. In 2022 Si Chen et al. [67] focused on Bitcoin price movements within a 1 hour time horizon integrating Blockchain data as the primary input feature for their proposed Deep Learning based model.

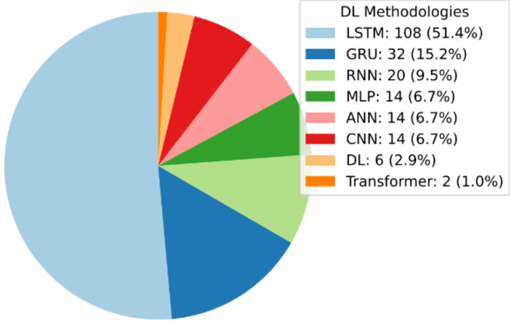

Figure 11. Pie chart of methodology wise distribution in Deep Learning studies.

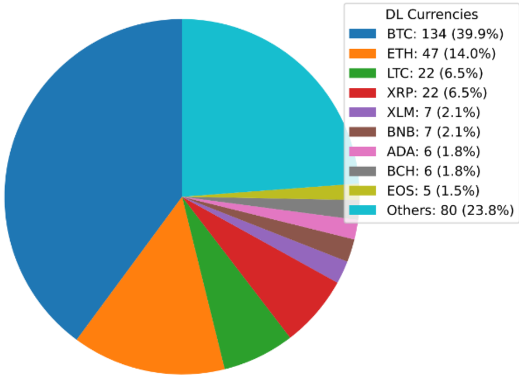

Figure 12. Pie chart of currency wise distribution in Deep Learning studies.

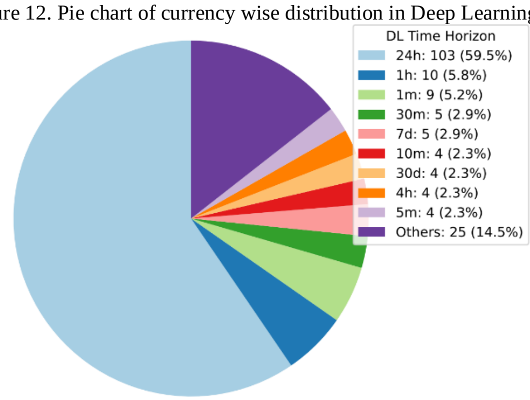

Figure 13. Pie chart of time horizon wise distribution in Deep Learning studies.

In 2017 a study conducted by Indra et al. [68] introduced a Multi Layer Perceptron base prediction model designed to forecast Bitcoin price over 24 hours. In 2022 Chuen et al. [56] and Stanley et al. [34] conducted research studies aimed at predicting the price of Bitcoin within a 24 hour time horizon employing Multilayer Perceptrons supplemented with various other Deep Learning methods. In 2023 Andres et al. [69] and Tiago et al. [70] conducted research studies dedicated to predicting the prices of various cryptocurrencies within a time horizon ranging from 1 to 24 hours utilizing the Multi layer Perceptron.

In 2023 a series of research studies were conducted by B et al. [71] BALCI et al. [49] Tenali et al. [72] Johari et al. [31] and Thanaya et al. [73] aiming to predict the prices of various cryptocurrencies primarily over a 24 hour time horizon leveraging sentiment analysis and price data encompassing LSTM. Carraro et al. [53] Zou et al. [74] Rubio et al. [70] and Sharma et al. [75] aimed to predict the prices of various cryptocurrencies over different time horizons employing LSTM. Lahmiri et al. [76] Zhang et al. [60] Zieba et al. [77] and KP et al. [46] focused on predicting the prices of various cryptocurrencies using price data employing a 24 hour price time horizon and exploring LSTM. Utama et al. [78] Mithab et al. [79] and PAVAN et al. [80] aimed to predict the prices of various cryptocurrencies primarily focusing on Bitcoin over a 24 hour time horizon employing LSTM. Chen et al. [81] utilized a combination of price data technical indicators data and external economic indicators data implementing LSTM. Pindza et al. [82] Mishra et al. [83] and Philip et al. [84] utilized price data implementing various Deep Learning methods including LSTM.

Gated Recurrent Units operate similarly to LSTM but require less computational overhead. In 2020 Jiang et al. [85] and Sun et al. [86] conducted research studies utilizing both price data and sentimental data implementing GRU. In 2021 Weinhardt et al. [19] employed technical indicators data sentimental data and blockchain data to make predictions over various time horizons including 1 minute 5 minute 15 minute and 60 minute utilizing GRU. Agarwal et al. [87] conducted a research study to predict the price of Dogecoin over a 24 hour time horizon using price data and sentimental data implementing GRU. Saini et al. [23] and Alabdulatif et al. [88] incorporated GRU along with other Deep Learning methods. In 2022 Aljadani et al. [89] Reddy et al. [90] Lim et al. [56] Farm et al. [91] and Khrustalovac et al. [92] employed GRU as part of their research methodologies predicting various cryptocurrencies over a 24 hour time horizon. Li et al. [93] conducted a research study to predict the price of Bitcoin over both 1 hour and 24 hour time horizons methodology including the use of price data and sentimental data. Palandoken et al. [94] conducted research to predict the prices of ETH over 15 minute and 30 minute time horizons utilizing price data incorporating GRU. Reddy et al. [90] utilized Lagged Data as their input feature for GRU developing a long short portfolio strategy. In 2023 B et al. [71] utilized both price data and sentimental data incorporating the use of GRU. J et al. [95] conducted a research study to predict the prices of BTC including GRU. Philip et al. [84] and Zieba et al. [77] conducted research studies aimed at predicting the prices of different cryptocurrencies over a 24 hour time horizon.

Transformers have recently gained prominence for their remarkable performance adapting well to non linear patterns via self attention mechanisms. In 2022 Crane et al. [96] aimed at predicting the prices of BTC and ETH over a 24 hour time horizon incorporating both price data and sentiment data into a Transformer model. Chatterjee et al. [97] focused on forecasting the values of SOL BTC and ETH utilizing Transformer models. Dorien et al. [98] conducted a research study to predict Bitcoin spikes leveraging whale alert data from Twitter implementing the Synthesizer Transformer model.

2) Deep Reinforcement Learning Approaches: Deep reinforcement learning brings a level of sophistication to cryptocurrency forecasting by combining neural networks with reinforcement learning principles. These algorithms learn optimal strategies through interactions with the environment making them well suited for dynamic and evolving cryptocurrency markets. The distribution of methodologies shown in Figure 14 unveils the prevalent algorithms employed. Proximal Policy Optimization Advantage Actor Critic and Deep Q Networks are the most utilized methodologies. Figure 15 indicates a notable portion of the research focuses on a 24 hour time horizon.

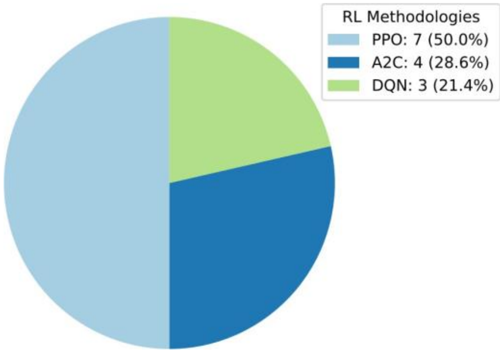

Figure 14. Pie chart of methodology wise distribution in Deep Reinforcement Learning studies.

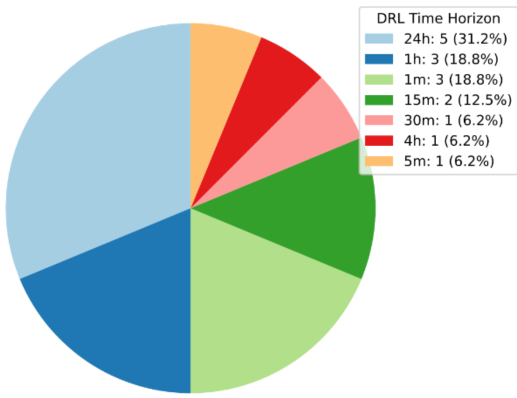

Figure 15. Pie chart of time horizon wise distribution in Deep Reinforcement Learning studies.

In 2022 Xiao et al. [99] addressed three prominent challenges confronting financial reinforcement learning the low signal to noise ratio of financial data survivorship bias and the issue of model overfitting during back testing. They introduced the FinRL Meta library actively maintained by the AI4Finance community which follows a DataOps paradigm collecting dynamic datasets from real world markets and transforming them into gym style market environments. In 2021 Carlos et al. [100] utilized price and blockchain data focusing on a 30 minute time horizon employing self attention network models achieving a notable profit percentage. Bo et al. [101] conducted a study employing Deep Evolutionary Reinforcement Learning Q learning and policy gradient centering around BTC with a 1 minute time horizon indicating that the evolution strategy outperformed other methodologies. Zeinab et al. [102] incorporated price data blockchain data and sentimental data in their study of Litecoin and Monero with a 24 hour time horizon utilizing daily samples with an 80 to 20 training and testing split. Denis et al. [103] focused on Q learning and DQN methods utilizing price data and technical indicators with Bitcoin indicating that all models outperformed a buy and hold strategy.

Pierre et al. [104] explored hierarchical reinforcement learning concepts by employing PPO A2C and TradeR models consistently achieving profits in a realistic environment even when transaction fees were involved. Jonathan et al. [105] employed PPO and A2C models demonstrating the superiority of the A2C algorithm over the PPO agent in terms of both the greatest return and the number of profitable experiments. Otabek et al. [106] utilized the DRL application neural model exploring swing trading scalping trading and a double cross strategy across BTC LTC and ETH with hourly time horizons achieving notable profits in just one month. Yun et al. [107] employed GAF CNN and PPO using ETH data revealing that transfer learning is suitable showcasing the adaptability of models in volatile market conditions. Shuyang et al. [108] applied an ensemble policy and buy hold strategy for automated cryptocurrency trading employing technical indicators outperforming the buy hold strategy achieving a substantial annualized return. Aisha et al. [109] employed PPO and CNN LSTM models with price data and technical indicators demonstrating adaptability in volatile market conditions. Vasileios et al. [110] explored algorithmic trading strategies using price data technical indicators and sentimental data focusing on a 1 hour time horizon emphasizing training TraderNet with the PPO algorithm.

Berend et al. [111] investigated algorithmic trading strategies by leveraging price data and technical indicators with PPO TD3 and SAC models focusing on a 5 minute time horizon evaluating the performance across various cryptocurrencies involving rigorous back testing. Cem et al. [112] employed price data as an input feature for Deep Double Q Learning Network buy hold and cointegration methods focusing on a 24 hour time horizon revealing the profitability of the Deep Reinforcement Learning strategy combined with the cointegration method in selecting pairs for crypto markets. Giorgio et al. [113] focused on utilizing price data in conjunction with Double Dueling Deep Q Networks models employing a 1 minute time horizon consistently yielding positive returns on average based on Double Q learning incorporating a Sharpe ratio reward function. Minh et al. [114] employed price data with Double Dueling Deep Q Networks Deep Q Network and Bayesian Optimization models utilizing a 15 minute time horizon revealing that the DDQN setting with the Sharpe ratio emerged as the most effective Q learning trading system.

Thanga et al. [115] employed a comprehensive dataset comprising price data blockchain data and sentimental data to develop and evaluate predictive models including a proposed Reinforcement Learning method integrated with a blockchain framework demonstrating superior performance. Stephan et al. [116] utilized price data and various reinforcement learning algorithms including Proximal Policy Optimization Advantage Actor Critic and Deep Q Network focusing on a 4 hour time horizon employing an 80 to 20 split ratio within the TensorTrade Python framework designed for creating specialized trading environments. Thomas et al. [117] employed a Direct Reinforcement Learning approach evaluating performance using the Sortino ratio focusing on cumulative returns and risk adjusted returns demonstrating that the DR model consistently outperformed a buy and hold approach. Yagna et al. [118] implemented a Deep Q Network model using both price data and bid ask data for a 1 minute time horizon constructing a historical order book representing a sequence of historical order book states to examine the DQN model performance in the context of high frequency trading.

3) Statistical Learning Approaches: Statistical models have a rich history in financial forecasting. The Autoregressive integrated moving average model is a fundamental Statistical method adept at analyzing and predicting time series data by incorporating the autoregressive differencing and moving average components. Generalized Autoregressive Conditional Heteroskedasticity models are pivotal tools renowned for their ability to model and forecast volatility. In the examined literature employing Statistical Learning a pie chart in Figure 16 reveals the distribution. ARIMA emerges as the most prevalent method.

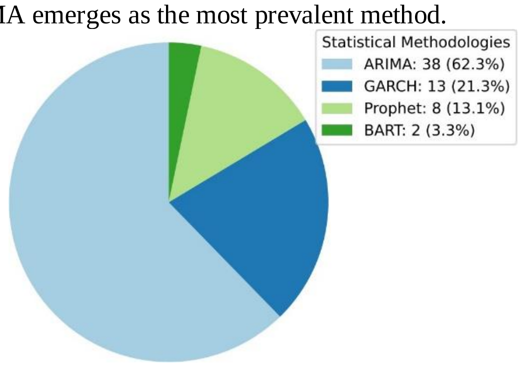

Figure 16. Pie chart of Forecasting Methods in Cryptocurrency Forecasting Literature Utilizing Statistical Learning.

Jayadi et al. [119] employed ARIMA models for cryptocurrency price prediction with a 24 hour time horizon focusing on BTC ETH BNB USDT and ADA evaluated using MAPE and RMSE indicating that the LSTM method outperforms the ARIMA method in terms of both accuracy metrics and visualization. Afif et al. [43] extended the ARIMA model by incorporating Exponential Smoothing and Time Series components for BTC price prediction emphasizing the potential for statistical methods to excel compared to artificial intelligence models in certain contexts. Iqbal et al. [55] utilized the ARIMA model with a specific focus on BTC price prediction over a 24 hour horizon encompassing RMSE Mean Absolute Error and R squared as key metrics. Dhavale et al. [120] presented a diverse approach by considering various models including Prophet ARIMA LSTM XGBOOST SVM LR and NB exploring a wider range of modeling techniques.

Ampountolas et al. [121] focused on ARIMA models for BTC with a 24 hour time horizon aligning with time series analysis methods. Azizib et al. [15] utilized ARIMA models for BTC price prediction with a 24 hour time horizon evaluating using RMSE and MAPE. Azizi et al. [10] applied ARIMA models for BTC price prediction aligning with the time series analysis approach. Desai et al. [122] utilized ARIMA models for BTC price prediction with a 24 hour time horizon. Ndunagu et al. [123] considered a wide range of cryptocurrencies in both SM and ARIMA models maintaining a focus on Statistical and time series analysis methods.

C. Social Data Exploration in Cryptocurrency Trends

This section explores how cryptocurrencies are talked about and searched for online looking at Google trends Reddit commentary and news article volumes to make sense of how online actions relate to market changes.

Looking at how people search for Bitcoin from 2019 to 2024 interesting patterns show up. In 2021 a lot of folks were really curious about Bitcoin because it experienced an all time high and the interest came back in 2022. Despite occasional fluctuations the overarching trend points to sustained growth in Bitcoin searches indicating a dynamic and evolving public interest.

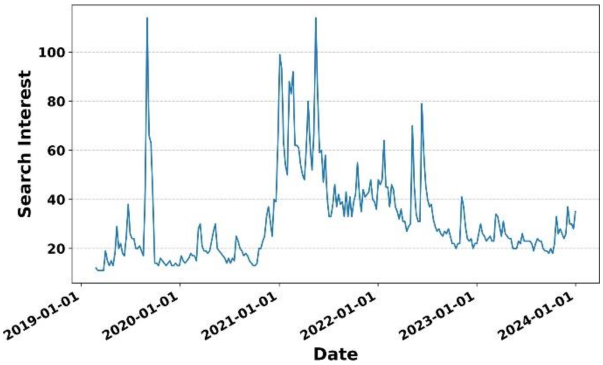

Figure 17. Google Bitcoin Trends Line Chart: Visual representation of search interest in Bitcoin indicating fluctuations in public curiosity.

The Reddit data specifically scraped from cryptocurrency related discussions provides valuable insights into the sentiments and trends within the cryptocurrency community. Notably starting from April 2022 a discernible trend emerges as the prices of Bitcoin begin to decline coinciding with an increase in Reddit comments discussing the cryptocurrency. This suggests a notable correlation between a decrease in Bitcoin prices and a rise in panic or engagement based Reddit discussions.

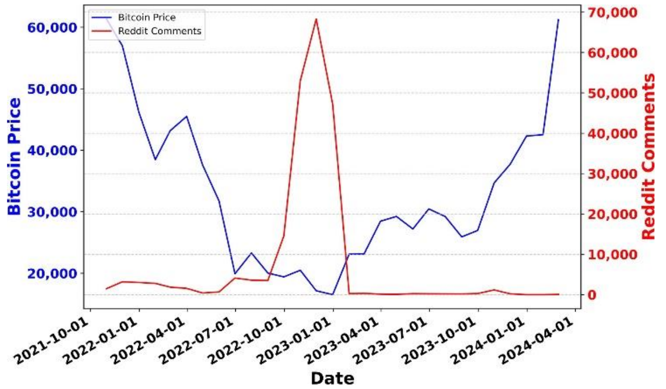

Figure 18. Reddit Comments vs. Bitcoin Prices showing the relationship between Reddit comments discussing Bitcoin and Bitcoin prices over time.

The analysis of cryptocurrency news articles spanning from June 2020 to December 2022 reveals a noteworthy correlation with Bitcoin prices. A substantial increase in Bitcoin prices is observed accompanied by a corresponding rise in the count of news articles particularly pronounced in 2021 when Bitcoin reached its all time high.

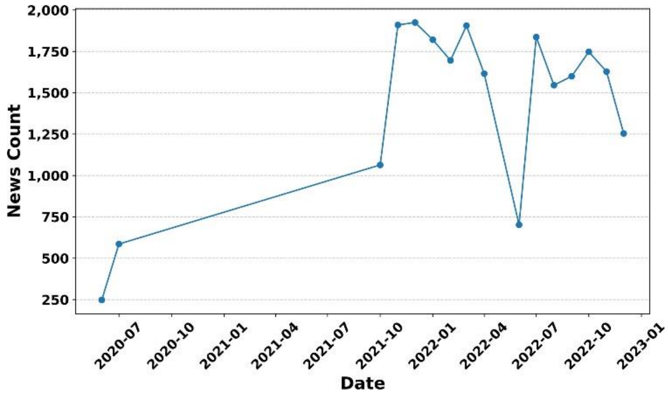

Figure 19. Monthly Cryptocurrency News Articles displaying the monthly count of news articles with notable peaks in late 2021 and mid 2022.

A comprehensive word cloud analysis based on a dataset encompassing various cryptocurrency keywords and corresponding tweet volumes spanning from April to December 2022 shows massive engagement. The total number of tweets for all keywords sums up to over 116 million suggesting a clear increase in conversations about digital currencies.

D. Case Study Insights: Back Testing versus Forward Testing

Cryptocurrency forecasting algorithms varying from traditional time series models like ARIMA to sophisticated Deep Learning techniques are designed to offer investors a predictive edge. However a disturbing reality emerges when these algorithms are released into the unforgiving waters of real time trading scenarios. Algorithmic strategies that seemed highly profitable during back testing often crumble resulting in financial losses and scrambled expectations for investors.

Figure 20. Showcases a word cloud analysis capturing the essence of Twitter discussions surrounding cryptocurrencies.

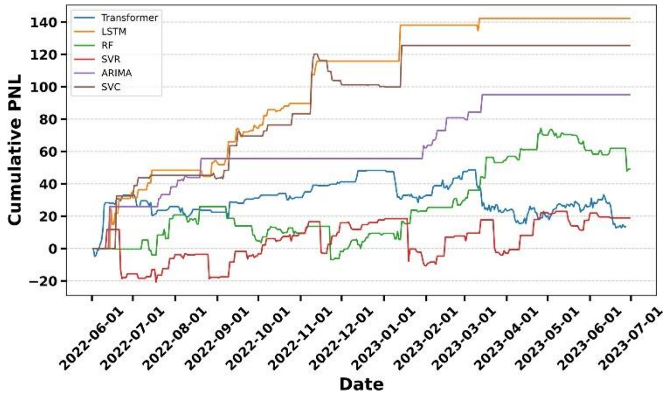

Figure 21. The y axis represents the cumulative profit and loss for each algorithm studied during the historical back test period.

Figure 21 illustrates the cumulative profit and loss of algorithms during the back test period spanning from the middle of 2022 to the middle of 2023. Across various predictive models a consistent accumulation of cumulative profit and loss is evident. These models collectively showcase notable proficiency in generating gains over the historical specified period.

Conversely Figure 22 displays the profit and loss of algorithms during forward testing covering the last six months of 2023. During this forward testing phase there was a dramatic shift in the observed dynamics. While some advanced ensemble models continued to maintain partial profitability traditional models struggled severely to sustain consistent gains. This divergence highlights the challenges and uncertainties that arise when transitioning from historical back testing to real world forward testing scenarios demonstrating the risk of model overfitting to historical noise.

E. Challenges and Open Problems

Cryptocurrency prediction is a challenging task faced by researchers who encounter various issues in their goal of accurate and reliable forecasts. Overfitting occurs when a model learns to perform well on the training data but fails to generalize to unseen data capturing noise rather than underlying patterns. Survivorship bias can skew the analysis by only considering successful cryptocurrencies that have survived until the present day leading to misrepresentation of risks.

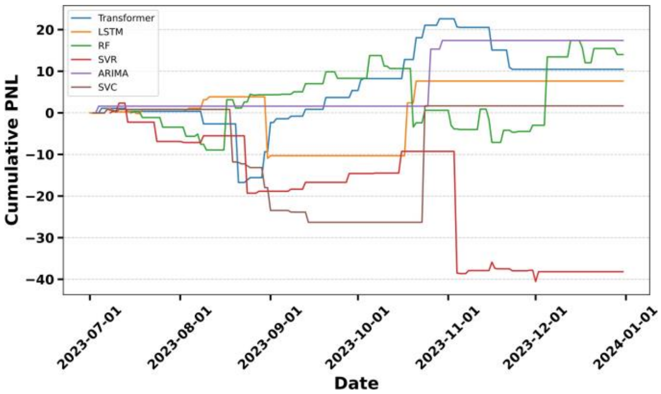

Figure 22. The y axis represents the cumulative profit and loss for each algorithm studied during the live out of sample forward testing period.

The quality and availability of data present significant challenges characterized by limited historical data data fragmentation across exchanges and the presence of outliers. Furthermore many models particularly those based on Deep Learning are considered black box models making it difficult to interpret their predictions raising concerns regarding model transparency and accountability.

Cryptocurrency markets are known for their high volatility driven by speculative trading regulatory developments and macroeconomic events. Forecasting accurate price movements in such volatile environments poses a significant challenge. Addressing stationarity challenges requires employing advanced time series modeling techniques such as differencing or regime switching models to capture the underlying dynamics of non stationary cryptocurrency price series.

V. CONCLUSION

This thorough survey paper extensively examines the complex world of cryptocurrency forecasting providing a detailed exploration of its challenges methodologies and trends. The results demonstrate that while Deep Learning techniques particularly Long Short Term Memory networks currently dominate the research landscape the practical implementation of these models remains highly complex. The empirical case study highlights the significant performance disparities between historical back testing and live forward testing emphasizing the critical need for robust models that generalize well beyond training environments avoiding the pitfalls of overfitting and survivorship bias. Furthermore the exploration of social data highlights the profound impact that public sentiment and news cycles have on cryptocurrency valuations. These findings extend the current understanding of financial modeling by demonstrating that modern forecasting must integrate multi modal data sources including price technical indicators and social sentiment to remain competitive. Future research must prioritize model interpretability and adaptability developing frameworks capable of adjusting to the rapid non stationary shifts characteristic of digital asset markets ensuring more reliable decision making for investors and stakeholders amid ongoing financial uncertainties.

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