

AN APPROACH TO IDENTIFY MACHINE LEARNING AND DEEP LEARNING METHODS AND DATA TO UNDERSTAND COMMON TIME VARIANT MODELS THAT CAN FORECAST BOTH CRYPTO CURRENCIES AND EQUITIES

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Abstract

Cryptocurrencies and Equity markets have been the most attractive investment in the modern world. While these are very attractive, they have been subject to a lot of volatility in their behaviour due to multiple reasons, such as macroeconomic conditions and regulation in various economic activities within countries and the world as a whole. There has been minimal research in this area to use Machine learning and deep learning approach to help predict the price of cryptocurrency and equities and other behaviours. There has also been very minimal research to understand the relationship on whether the change in the value of equities has an effect on the value of cryptocurrencies and vice versa. These effects are due to correlational causal or any other kind of relationship between the values of both the investment asset classes.

This research aims to identify models based on Machine learning and deep learning that can predict the price or value of cryptocurrencies and equities. Secondly, the study also aims to understand the effect of these two asset classes on each other with respect to their value under certain scenarios to understand if they share causal correlational or any other type of relationship, which is yet to be determined.

Introduction

Economies of the world are rapidly changing due to the advent of modern technology and digitalization across various business domains. More importantly, in the area of equities and cryptocurrencies. The virtualized nature of these assets helps manage, maintain, and track these assets with ease. These assets are time-variant and sensitive to other macroeconomic and geopolitical conditions across the world. These also depend on both short-term and long-term trends and events that occur across the globe. Other factors include the country's laws, decisions taken by respective governments and regulatory bodies such as SEC and Central Banks. The value of equities and cryptocurrencies is also impacted by specific factors such as their utility or domain under which the company or the currency is listed. As suggested by Tripathi (2014). It is also important to investigate whether, under certain volatile scenarios, the change in equity price or change in the index (global benchmark indices) has a correlated or causal effect on the price of a cryptocurrency or vice versa.

Since there are so many factors and the data related to these factors is available in some form as both primary and secondary sources. An interesting area of research is to explore to use of Machine learning and, Deep learning to understand the behavior and forecast the value of time-variant assets such as stocks, indices and cryptocurrencies. The advantage of using modelling approaches is that it can help the stakeholders of the financial domain to predict the price and behavioral trends of cryptocurrencies and stocks. However, another advantage is that the approaches are learning-based and strongly data-driven due to the data-driven nature of these models. These can help understand the behaviour or forecast the values close to reality with a minimal degree or margin of error.

Problem Statement

The following research questions will be addressed in the Research:

1. What are the Machine learning, Deep learning and Time Series models best suited for forecasting short-term and long-term cryptocurrency prices?
2. What are the Machine learning, Deep learning and Time Series models best suited for forecasting short- and long-term equity prices?
3. What are the Machine learning, Deep learning and Time Series models best suited for forecasting short-term and long-term upside and downside behaviour for cryptocurrencies?
4. What are the Machine learning, Deep learning and Time Series models best suited for forecasting short-term and long-term upside and downside behaviour for equities?

Objectives

The aim of the research is to identify a set of Machine learning and deep learning models and approaches that can be used to predict cryptocurrency and equity prices. It also includes the study of methods to identify causal or any other type of relationships between cryptocurrencies and equity prices. This will help in achieving the following objectives

1. Building the knowledge on the right set of machine learning and deep learning methods that can be used for determining the price or behavior of cryptocurrencies and equities in advance.

Prediction of Cryptocurrency price and behaviour using Machine Learning and Deep learning

According to Milosevic (2016), estimating the long term value of equities is a complex task. He aims to predict the equity's long term value using machine learning approaches. Findings from the experiments show that the proposed approach can predict whether the price will be at least higher by 10% or not over a horizon of one year. The metric used to measure the performance of the model is F1 -score. It is also observed that the approach can predict correctly in 76.5% of the scenarios. The author also mentions the limitation of the approach to be fixing the duration of data used for modelling and not being able to capture the dynamic behaviour and the variations in markets that occur over time.

According to Ganapathy and Neogy (2017), cryptocurrency price behaviour could be predicted using machine learning methods. Their study used the data from crypto-related news and information from channels such as social media feeds, historic prices of cryptocurrencies, and information from microblogging sites such as Twitter. However, the authors could not conclude on the improvement achieved with respect to predicting the behaviour of the cryptocurrency prices. Though the work emphasises the importance and use of machine learning in this area. It does not quantify the benefits of their approach.

According to Hitam and Ismail (2018), Support Vector Machine (SVM) L. Wang (2005) worked well for forecasting cryptocurrency compared to the state of the art approaches of the past. However, they highlight the scope for improvement of accuracy in scenarios where there was inadequate treatment and understanding of data when sample sizes were small. Hence, their work

focuses on improving the accuracy of the forecast of cryptocurrency prices in such scenarios. The authors further test their proposed approach with six cryptocurrencies using different models. They conclude that the use of SVM in combination with their approach provided an accuracy of 95.5% compared with the forecast results for one year. Additionally, it is also observed that using their proposed approach, the SVM model had the lowest MAPE, which was used to compare the margin of errors.

According to Alessandretti (2018), hypothesis testing could be used along with existing standard machine learning models to predict cryptocurrency prices to generate profits. The authors use the cryptocurrency daily prices from November 2015 to April 2018. The authors claim that their proposed approach works well for the short term cryptocurrency market. An important observation in this research is that all the cryptocurrencies were standardized and expressed as Bitcoin. Machine learning methods such as gradient boosting decision trees Si et al. (2017) seem to work exceptionally well with short term intervals of 5 to 10 days, and deep learning methods such as LSTM Hochreiter and Schmidhuber (1997) worked well for longer intervals. The limitation of their approach is that it does not consider the prices from different exchanges. The second limitation is using average price values rather than the price captured at regular intervals at different times of each day.

According to Altan et al. (2019), forecasting cryptocurrency prices is very important. Also, they believe that a single model is not enough to forecast the prices of cryptocurrencies with great accuracy. Furthermore, they believe that the single model-based approaches cannot provide the best forecasting solution at all times. Hence, they propose a hybrid approach that uses the LSTM neural network and Empirical Wavelet Transform-based decomposition with cuckoo search.

Experiments were conducted with the hybrid model for four cryptocurrencies such as BTC, XRP, DASH, and LTC. They claim that the proposed hybrid model had superior performance due to the ability of their hybrid model to capture non-linear properties arising over time. On the contrary, the authors do not clearly explain or highlight the improvement in accuracy or any other mathematical metric that could be used to assess the superiority of the hybrid model-based approach over the single model-based approach.

According to Bai et al.(2019), price prediction and upward and downward trends for cryptocurrencies could be accurately predicted using machine learning. They used price data of 21 cryptocurrencies from coinmarketcap.com. Furthermore, they tried to accurately predict the upward or downward trend of cryptocurrencies for the current day using historic data of the previous day. They also use other factors such as the price sentiment of benchmark indices. Additionally, a combination of similarity metrics and classification methods was used to compare different cryptocurrencies' features. It was observed that their approach improves prediction performance ranging from 0.4 to 17.8%. These results were observed for most of the cryptocurrencies among the chosen 21 cryptocurrency types.

According to Livieris et al. (2020), ensemble averaging and bagging(Bühlmann, 2012) using deep learning models such as LSTM and Bi-directional LSTM by Graves et al. (2005) can be used to forecast the cryptocurrency prices. They use the model stacking method to solve two objectives: first, to predict the cryptocurrency price for the next one hour and second (to classify) find out if the cryptocurrency price will move up or down. It was observed that ensemble learning by combining deep learning methods had helped in gaining a stable model for

forecasting cryptocurrency prices. The authors also mention that the limitation of their approach is increased time for training and increased computational cost. Due to this limitation, they mention that the model in its current form cannot be used in real-time environments. The research further emphasises the need to further investigate the scenarios of crypto currency price prediction such as times of high unpredictability and instability in financial and crypto currency markets. The authors in future propose to investigate further to use Anomaly detection methods to handle unpredictable and volatile scenarios.

According to Poongodi et al. (2020), cryptocurrency has fascinated the world for the last decade. They believe the untraceable and uncontrollable nature of cryptocurrencies makes it very interesting for many people around the world. They try to predict the price of ether-based on the historical prices. They use two machine learning methods: linear regression and Support Vector Machine. The data used for modelling is the time-series data of the daily opening and closing prices of Ethereum. Their experiments show that SVM proved to be the best performing model among the two chosen models, with an accuracy score of 96.06%. The linear regression model had an accuracy score of 85.46%. However, an important observation that they highlight is that the LR model provides higher accuracy with large dataset sizes. They also conclude that by adding additional features while training SVM, its accuracy compared to the LR model increased from 10.62% to 13.54%.

According to Parekh et al. (2022), cryptocurrency prices are very unstable. They are stochastic in nature. The authors analyse the sentiment of tweets and information from different social media platforms. They also consider the interdependencies of similar cryptocurrencies on each other.

Further, they also use historic prices to predict cryptocurrency prices. The experiments are conducted with two cryptocurrencies, and the proposed approach is found to be more robust and performant compared to the existing approach based on sentiment analysis.

Prediction of Equity price and behaviour using Machine Learning And Deep learning

According to Adebisi et al. (2014), ARIMA models and Artificial Neural Networks are referred in multiple literatures to predict the stock prices and claim superiority of performance with ANN models. So the authors try to study both the models to identify the best model amongst the two and validate the claim of the previous literatures. They use the already available data from New York Stock exchange. When ARIMA and ANN approaches are compared side by side, it is found that both perform well in the context of stock price prediction. However, the ANN-based model seems to have better performance than ARIMA models though the forecasted values are very close to actual values in both ARIMA and ANN-based modelling scenarios.

According to Milosevic (2016), estimating the long term value of equities is a complex task. He aims to predict the equity's long term value using machine learning approaches. Findings from the experiments show that the proposed approach can predict whether the price will be at least higher by 10% or not over a horizon of one year. The metric used to measure the performance of the model is F1 -score. It is also observed that the approach can predict correctly in 76.5% of the scenarios. The author also mentions the limitation of the approach to be fixing the duration of data used for modelling and not being able to capture the dynamic behaviour and the variations in markets that occur over time.

According to J. Wang et al. (2018), a one-dimensional Convolution Neural Network (1D-CNN) could be used to predict the price of equities. The implemented model did not use standard technical indicators. Instead, it extracted important features and patterns from the data by understanding the data with respect to time and multiple other parameters such as price and volume. The authors also mentioned that their model is tested with data and uses only six parameters. The experiments are conducted using equity data from January 2010 to October 2017. their approach did not depend on technical indicators and was found to be more robust and profitable than the old state of the art machine learning approaches of the past. It is observed that the proposed model outperforms the state-of-the-art model in a range between 12.4 to 63.3% and the achieved profitability in terms of annual return in the range of 99% -245% when compared with other approaches.

According to Ampomah et al. (2020), it is possible to predict the direction (upwards or downwards) of stock prices or benchmark indices so that investors can reduce the risk of investment. The authors evaluate tree-based ensemble models like Random Forest, XGBoost, Bagging classifier, AdaBoost and Extra tree classifier and Voting Classifier. The use of the datasets by randomly choosing from NYSE NSE and NASDAQ. They evaluated the models for F1, precision, recall, specificity and accuracy and K fold cross-validation with K=10 to evaluate the models. The experiments conducted found that AdaBoost performed well with training data. However Extra tree classifier outperformed other models with respect to all the metrics compared to other tree-based models used in their study. The authors also highlighted the limitation of their study as the restricted scope of only experimenting with tree-based models, secondly not using regularisation and other techniques.

According to Nabipour et al. (2020), the stock price prediction problem can be solved as a regression problem. The authors created four different stock groups. The groups are a set of stocks that belong to the same sectors. Four different stock groups represent four different sectors. Furthermore, ten years of historic data was used to analyse and train the models. At least technical indicators of these stock groups are used as input to train the models. The neural network models comprise ANN, Recurrent Neural Network (RNN) and LSTM. Additionally, some tree-based models are also chosen for training and evaluations. These include Decision Tree, Random Forest, AdaBoost and XGBoost. These models are used to forecast daily, weekly, fortnightly, and monthly advanced futuristic predictions. The experiments concluded that LSTM was the best performing model compared with other chosen models under the study. However, the limitation was that the time taken for the prediction was very high, i.e., 80 milliseconds.

According to Mehtab and Sen (2020), predicting the future price of stocks and indices is a matter of research for many stakeholders. The authors propose a hybrid approach using machine learning and deep learning techniques. They evaluate at least eight classification and regression techniques which are either based on machine learning or deep learning. They choose three-year data from 2015 to 2018 for the NIFTY 50 Indian benchmark indices. They predict the closing values of the NIFTY index and movement patterns. To find out the movement patterns, they use a number of classification models of machine learning. For forecasting the index closing value, a CNN-based Neural network model for regression is used. They also augment the CNN-based model with a known technique as walk-forward validation. Additionally, both univariate and multivariate approaches and network configurations are applied. They use a horizon of 5 days to

forecast the NIFTY 50 index values in a chosen year of 2019. The CNN based model is tuned, and at least three approaches with different variables are used. Factors such as the number of sub-models used with the model and varied training data size are also considered. Extensive experiments and metrics related to classification and regression performance are captured. The findings clearly show that the CNN-based model with multivariate forecasting capability is successful in accurately predicting the NIFTY 50 index values for a weekly horizon. They also conclude that deep learning methods perform far better than machine learning methods, and multivariate methods provide better forecasting abilities than univariate methods. The authors would also like to evaluate Generative Adversarial Networks (GAN) in the context of forecasting NIFTY 50 stock price and movement predictions in the future.

Understanding Correlation Causal and other relationship between Cryptocurrencies and Equities

According to Gurrib et al. (2019), energy based currencies can be useful to diversify the equity portfolio that only contains energy stocks of the US S&P composite 1500 benchmark index. The author uses different models such as ARMA-GARCH and machine learning methods to model the volatility to help make stakeholders better investment decisions. Different ARMA models and machine learning models are assessed using the daily data between November 21st, 2017, and January 31st, 2019. Findings from the research showed that there was no significant improvement in the energy equity portfolio moreover, the energy-based cryptos did not perform well, as a result of which the cryptos did not contribute to improving the returns of the US energy-based stock portfolio.

According to Dahir et al. (2020), The information on the relationship between the volatility of bitcoin returns and equity markets remains unavailable in emerging markets, mainly BRICS countries. The author tries to use the data between 01st Jan 2012 and May 31st 2012 to understand the connectedness between bitcoin and the equity market. The authors propose using a TVP- VAR model, which uses a time-variant vector parameter to compliment the VAR model. The findings identify that bitcoin returns do not create variations in the volatility of equity markets in BRICS countries; however, the vice-versa is true. The authors also conclude that TVP-VAR is very good at modelling the volatility connectedness in the financial domain and justifies the model's use in the scenario explained above.

According to Kim et al. (2020), under high volatility conditions such as the COVID-19 pandemic. It is computationally difficult to understand the time-variant relationships between cryptocurrencies, US stock markets and the gold markets. They use the GARCH-DCC, Nonlinear Asymmetric GARCH DCC, Gaussian copula-based GARCH-DCC (GC-DCC) and Gaussian copula-based Nonlinear Aysymmetric DCC (GCNA-DCC) to understand the relationship between bitcoin, gold and US stock market namely the S&P 500 benchmark. Their experiments show that the relationship between different types of assets under the study is statistically significant with respect to the volatility and the logarithm of the return. They also found that copula-based GARCH-DCC models were able to overcome the computational difficulty and were also able to capture the time-variant relationships and volatility across the assets considered in the study. However, they also mention the limitation of their approach as not to be multivariate data-based analysis. The authors would like to improve this aspect in their future work.

According to Xunfa et al. (2020), their study uses causal analysis to understand the relationship between cryptocurrencies and stock markets. They use two methods, namely Granger causality and Liang causality, to analyse the relationship. It is found that either the equity market or the cryptocurrency market does not have any characteristics of Granger causality. However, they find short-run unidirectional temporal causality between cryptocurrency markets and emerging stock markets and a long-run unidirectional causal relationship when both the markets are stable. In other words, these relationships change from time to time at different intervals. Specifically, when there is volatility and swings, there is a unidirectional causal relationship between the cryptocurrency market to the emerging market. However, when both the markets stabilize, they behave very independently relative to each other. Yet another observation was that as the cryptocurrency market grows exponentially, they get connected steadily to the emerging equity markets.

According to Zeng et al. (2020), their research helps understand the critical implications of the financial markets on bitcoin returns. They use the VAR methodology to understand the interdependence between bitcoin returns and other assets such as equities, gold and oil. Their experiments show that the connectedness of bitcoin and other assets is weak. They also perform a rolling window analysis and find that when a negative return is obtained, the connectedness is more substantial when compared to obtaining a positive return. They also claim that their results are stable and reliable when applied on other cryptocurrencies such as Ethereum and Ripple.

According to Soloviev et al.(2020), it is interesting to understand the indicators of critical and crash phenomena in cryptocurrency and stock markets in volatile scenarios .they try to construct indicators by combining empirical cross-correlation with the help of Random Matrix theory. The research tries to understand the cross-correlation, the distribution of eigenvalues and the eigenvectors for both the cryptocurrency and the equity markets. They use the time-series of daily price returns of both the cryptocurrency and the stock markets. The approach shows that the largest eigenvalue can determine the overall scenario and is directly related to a crash scenario. Hence, they conclude that the largest eigenvalue for the matrix of correlation for both the markets can forecast the fall in both the cryptocurrency and the stock markets.

According Chasiotou. (2020), the complexity of understanding the relationship between bitcoin prices and stock market indices has drawn attention of many researchers, investors, and other stakeholders. The author tries to create a model to predict the price of bitcoin with the best possible accuracy. The author uses data from different stock indices and some companies with huge market capital. The results show that the best forecasting model had an accuracy of 56.2 per cent. An important aspect of the algorithm is that it uses an algorithm ensemble. The limitation of the approach is that it could not very accurately predict the price of bitcoin for the next day using current-day information. The author also mentions that their technique identified that only big companies were present in the Asian market scenario. He also recommends considering indices from global markets and considering the mix of large and small market capitalization companies and many other factors to be taken into account for future research.

According to Singh and Singh (2021), there has been significant market capitalization in the cryptocurrency market. As a result, this may potentially impact the equity market. They try to study if there is a strong correlation between bitcoin price and the equities that are part of the Dow Jones Industrial Index using correlation. Their findings identified that there was a strong correlation between the price of some equities that could affect the price of bitcoin. However, a causal relationship indicating if a change in the price of equities would affect the price of cryptocurrencies could not be established successfully.

According to Kymäläinen, (2021), cryptocurrencies and other types of speculative assets such as gold and equities have a minimal correlation. However, they also believe that price and volatility behaviours are not thoroughly understood in terms of similarities and correlations.

Their research tries to understand the connectedness between speculative assets and the return and volatility of cryptocurrencies. They use statistical methods such as variance decomposition, rolling samples, multi wavelet correlations, robustness verification using grangers causality and hypothesis testing methods based on significance levels to validate the connectedness (interrelationships). The findings of their experiments show that some cryptocurrency price behaviour has a relationship with assets like gold. In another experiment, they found that there are miniscule dependencies on the equities of the technology sector. Finally, there is a correlation between cryptocurrencies themselves in some scenarios.

According to Umar et al. (2021), investors, regulators of financial markets, and other stakeholders have a lot of interest in cryptocurrency markets. They investigate the connectedness between the technology sector and the cryptocurrency markets. They use the data between 1st august 2014 and 31st october 2018. they use techniques such as Wavelet local multiple

correlations. They also measure the connectedness using static and rolling window analysis with several technology sectors and cryptocurrency markets. Their research shows a lack of connectedness between cryptocurrency markets and technology sectors. However, they identify that government regulations cause significant fluctuations in a few crypto currency prices. Further they also recommend the study of non-parametric methods to understand and measure the connectedness of technology sectors with cryptocurrency markets as a future area of their research.

According to Iyer (2022), crypto assets have been the most popular asset class among investors. There has been gradual adoption in many countries. However, they believe that extreme price volatility has raised concerns, particularly in emerging markets. The authors aim to estimate the spillovers between equity and cryptocurrency markets mainly from the United States daily data on returns and price volatility. They use popular cryptocurrencies such as bitcoin and tether and S&P500 and MCSI indices of the equity market. The findings from the study show that both equity and crypto markets have become greatly interconnected. They also find that the equity indices have increased 12 to 16 per cent ever since the covid pandemic. They also conclude that spillovers from the tether to equity market led to 4 to 6% variation, and spillovers from bitcoin to equity market have led to 14- 18% variation in volatility of equity prices. This has also led to a variation of equity returns in the range of 8 to 12%.

AI Algorithms That can be used for Prediction and Causal Inference

MA (Moving Average)

The Moving Average (MA) model smooths the time series data by averaging past observations over a specified window. This method helps to capture the overall trend of the asset prices by reducing noise and fluctuations. In cryptocurrency and equity forecasting, MA is used to track long-term price trends by filtering out short-term variations in the market.

EMA (Exponential Moving Average)

The Exponential Moving Average (EMA) is a variation of the MA model that gives more weight to recent observations, making it more sensitive to the latest data points. In cryptocurrency and equity forecasting, EMA is used to track the most recent trends and react faster to market changes, providing timely insights into price movement.

Model/Algorithm	Type	Details
MA	Statistical Model	Tracks price trends and smooths fluctuations
EMA	Statistical Model	Reacts quickly to recent price changes and trends
ARIMA	Statistical Model	Predicts future values based on past price patterns
SARIMA	Statistical Model	Handles seasonal fluctuations and periodic trends
SARIMAX	Statistical Model	Includes external factors for predictions
RNN	Deep Learning	Captures dependencies in sequential data
LSTM	Deep Learning	Models historic relationships and complex patterns
GRU	Deep Learning	Efficiently captures dependencies while reducing complexity
Granger Causality	Linear Causality	Identifies predictive relationships between assets
Transfer Entropy	Linear Causality	Measures directional causality between two assets
CCM	Non-linear Causality	Detects non-linear causal relationships between variables

ARIMA (AutoRegressive Integrated Moving Average)

ARIMA is a popular statistical model that combines autoregressive (AR) and moving average (MA) components with differencing to make the data stationary. In cryptocurrency and equity forecasting, ARIMA is used to predict future asset prices based on the patterns of past values and the errors in previous predictions, making it effective for capturing trends over time.

SARIMA (Seasonal AutoRegressive Integrated Moving Average)

SARIMA extends the ARIMA model by incorporating seasonal components to handle periodic patterns in the data. In cryptocurrency and equity forecasting, SARIMA is useful when asset prices exhibit regular seasonal behavior, such as monthly or yearly cycles, allowing for more accurate predictions during specific time intervals.

SARIMAX (Seasonal AutoRegressive Integrated Moving Average with Exogenous Variables)

SARIMAX is an extension of SARIMA that incorporates external variables (exogenous variables) in the forecasting process. In cryptocurrency and equity forecasting, SARIMAX is useful when market prices are influenced by external factors, such as economic indicators or events such as critical like global changes to natural or manmade events such as epidemics and manmade errors that add as key drivers, allowing the model to account for these influences alongside past price data.

RNN (Recurrent Neural Network)

Recurrent Neural Networks (RNNs) are deep learning models designed to process sequential data by using information from previous time steps to predict future values. In cryptocurrency and equity forecasting, RNNs are effective at capturing temporal dependencies and modeling complex patterns in asset price movements over time, providing accurate predictions based on historical data.

LSTM (Long Short-Term Memory)

LSTM is a type of RNN designed to address the vanishing gradient problem by using memory cells to store long-term dependencies in the data. In **cryptocurrency** and **equity** forecasting, LSTM networks are powerful for modeling long-term relationships and capturing complex patterns in asset prices, making them suitable for forecasting in volatile and fluctuating markets.

GRU (Gated Recurrent Unit)

Gated Recurrent Units (GRUs) are a variant of RNNs that simplify the memory structure by using fewer gates to control information flow. In **cryptocurrency** and **equity** forecasting, GRUs are more computationally efficient than LSTMs while still being able to capture long-term dependencies in time series data, offering a balance between performance and efficiency in forecasting tasks.

Granger Causality Test

The **Granger Causality Test** is a statistical hypothesis test that determines whether one time series can predict another. It tests whether past values of one asset, such as stock prices, can help forecast future prices of another asset, like cryptocurrency. In forecasting, this test is valuable for identifying potential relationships where changes in one asset lead to changes in another.

Transfer Entropy

Transfer Entropy is a measure of the directional flow of information between two time series, helping to identify causality in dynamic systems. In **cryptocurrency** and **equity** forecasting, transfer entropy is used to analyze whether the price movement of one asset (e.g., a stock) influences the price movement of another asset (e.g., cryptocurrency), capturing information transfer from one market to another.

Non-Linear Causality Algorithm:

Convergent Cross Mapping (CCM)

Convergent Cross Mapping (CCM) is a non-linear causality detection method that identifies causal relationships between time series in complex, dynamic systems. CCM works by testing whether one time series can predict the state of another time series in a non-linear manner. In **cryptocurrency** and **equity** forecasting, CCM is particularly useful for identifying relationships where traditional linear models, such as Granger causality, may fail to capture the underlying nonlinear interactions.

Common Metrics for Time Series and Deep Learning Models

3.6.1 Mean Absolute Error (MAE)

MAE measures the average of the absolute differences between the predicted and actual values. It is commonly used to evaluate the accuracy of both time series and deep learning models by quantifying the average prediction error.

$$MAE = (1/n) * \sum |y(t) - \hat{y}(t)|$$

Where:

- $y(t)$ = Actual value at time t
- $\hat{y}(t)$ = Predicted value at time t
- n = Total number of data points

Mean Squared Error (MSE)

MSE calculates the average of the squared differences between predicted and actual values. It is also widely used to evaluate the performance of both time series models and deep learning models.

$$MSE = (1/n) * \sum (y(t) - \hat{y}(t))^2$$

Where:

$y(t)$ = Actual value at time t

$\hat{y}(t)$ = Predicted value at time t

n = Total number of data points

Root Mean Squared Error (RMSE)

RMSE is the square root of the Mean Squared Error (MSE). It provides the error in the same units as the original data, making it easier to interpret in practical terms, which is particularly useful in time series forecasting.

$$RMSE = \sqrt{[(1/n) * \sum (y(t) - \hat{y}(t))^2]}$$

Where:

- $y(t)$ = Actual value at time t
- $\hat{y}(t)$ = Predicted value at time t
- n = Total number of data points

Datasets for Equity Modeling

Most of our research will use data from publicly available data sources. We have tried to gather data for different benchmark indices in our study. We have considered data for NASDAQ, The US equity index, NIFTY 50, NIKKEI JAPAN DAX and S&P 100. The data gathered is the historical data of 7years . We have the data for daily and weekly intervals. All the datasets from equity benchmarks have common attributes such as high, low, open, close and volume. The data is available in character-separated variable format (CSV).

Datasets for Crypto Currency Modeling

In our research, we will use the historic data of Bitcoin.As explained in the previous section. We would consider the historical data 7 years having the same set of common attributes and the duration of years between 2015 to 2022.

Sources of Data.

Following is the detailed list of assets and their data sources used for our study

Topic	Type of Asset	Source
NIFTY50 Index India	Equity	Yahoo Finance web portal
DAX Index Germany	Equity	Yahoo Finance web portal
NASDAQ 50 Index USA	Equity	Yahoo Finance web portal
NIKKEI JAPAN	Equity	Yahoo Finance web portal
S&P 100	Equity	Yahoo Finance web portal
Bitcoin USD Price data	Cryptocurrency	Yahoo Finance web portal

Assumptions for definition of Longterm and Shortterm in our study

In our study Short term is defined as a period between 3 months to 12 months and long term is defined as a period beyond 12 months. In our study we will not be considering the interval less a day.

BIBLIOGRAPHY

Adebiyi, A. A., Adewumi, A. O., & Ayo, C. K. (2014). Comparison of ARIMA and artificial neural networks models for stock price prediction. *Journal of Applied Mathematics*, 2014.

Alessandretti, L., ElBahrawy, A., Aiello, L. M., & Baronchelli, A. (2018). Anticipating cryptocurrency prices using machine learning. *Complexity*, 2018.

Altan, A., Karasu, S., & Bekiros, S. (2019). Digital currency forecasting with chaotic meta-heuristic bio-inspired signal processing techniques. *Chaos, Solitons & Fractals*, 126, 325–336.

Ampomah, E. K., Qin, Z., & Nyame, G. (2020). Evaluation of tree-based ensemble machine

learning models in predicting stock price direction of movement. *Information*, 11(6), 332.

Bai, C., White, T., Xiao, L., Subrahmanian, V. S., & Zhou, Z. (2019). C2P2: a collective cryptocurrency up/down price prediction engine. *2019 IEEE International Conference on Blockchain (Blockchain)*, 425–430.

Bühlmann, P. (2012). Bagging, boosting and ensemble methods. In *Handbook of computational statistics* (pp. 985–1022). Springer.

Chasiotou, V. (2020). Directional classification of cryptocurrencies using stock indices: the case of Bitcoin.

Dahir, A. M., Mahat, F., Noordin, B.-A. A., & Ab Razak, N. H. (2020). Dynamic connectedness between Bitcoin and equity market information across BRICS countries: Evidence from TVP-VAR connectedness approach. *International Journal of Managerial Finance*.

Ganapathy, A., & Neogy, T. K. (2017). Artificial Intelligence Price Emulator: A Study on Cryptocurrency. *Global Disclosure of Economics and Business*, 6(2), 115–122.

Graves, A., Fernández, S., & Schmidhuber, J. (2005). Bidirectional LSTM networks for improved phoneme classification and recognition. *International Conference on Artificial Neural Networks*, 799–804.

Gurrib, I., Elshareif, E. E., & Kamalov, F. (2019). The Effect of Energy Cryptos on Efficient Portfolios of Key Energy Companies in the S&P Composite 1500 Energy Index. Gurrib, I., Elshareif, EE & F. Kamalov (2019). The Effect of Energy Cryptos on Efficient Portfolios of Key Energy Listed Companies in the S&P Composite, 1500, 179–193.

Hitam, N. A., & Ismail, A. R. (2018). Comparative performance of machine learning algorithms for cryptocurrency forecasting. *Ind. J. Electr. Eng. Comput. Sci*, 11(3), 1121–1128.

Hochreiter, S., & Schmidhuber, J. (1997). Long short-term memory. *Neural Computation*, 9(8), 1735–1780.

Iyer, T. (2022). Cryptic connections: spillovers between crypto and equity markets. *International Monetary Fund*.

Kim, J.-M., Kim, S.-T., & Kim, S. (2020). On the relationship of cryptocurrency price with us stock and gold price using copula models. *Mathematics*, 8(11), 1859.

Kymäläinen, J. (2021). Cryptocurrency Market's Effect on Speculative Assets such as Technology Stocks and Gold: Evidence from Europe.

Livieris, I. E., Pintelas, E., Stavroyiannis, S., & Pintelas, P. (2020). Ensemble deep learning models for forecasting cryptocurrency time-series. *Algorithms*, 13(5), 121.

- Mehtab, S., & Sen, J. (2020). Stock price prediction using convolutional neural networks on a multivariate timeseries. ArXiv Preprint ArXiv:2001.09769.
- Milosevic, N. (2016). Equity forecast: Predicting long term stock price movement using machine learning. ArXiv Preprint ArXiv:1603.00751.
- Nabipour, M., Nayyeri, P., Jabani, H., Mosavi, A., & Salwana, E. (2020). Deep learning for stock market prediction. *Entropy*, 22(8), 840.
- Parekh, R., Patel, N. P., Thakkar, N., Gupta, R., Tanwar, S., Sharma, G., Davidson, I. E., & Sharma, R. (2022). DL-GuesS: Deep Learning and Sentiment Analysis-based Cryptocurrency Price Prediction. *IEEE Access*, 10, 35398–35409.
- 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.
- Si, S., Zhang, H., Keerthi, S. S., Mahajan, D., Dhillon, I. S., & Hsieh, C.-J. (2017). Gradient boosted decision trees for high dimensional sparse output. *International Conference on Machine Learning*, 3182–3190.
- Singh, G. B., & Singh, K. (n.d.). Analyzing Trends in Variations of Dow Jones Stocks and Cryptocurrency Prices. Name Page No. Analyzing Trends in Variations of Dow Jones Stocks and Cryptocurrency Prices, 5.
- Soloviev, V., Yevtushenko, S., & Batareyev, V. (2020). Comparative analysis of the cryptocurrency and the stock markets using the Random Matrix Theory.
- Tripathi, L. K., Parashar, A., & Jaiswal, S. (2014). Impact of macroeconomic variables on sectoral indices in India. *Pacific Business Review International*, 6(12), 83–90.
- Umar, Z., Trabelsi, N., & Alqahtani, F. (2021). Connectedness between cryptocurrency and technology sectors: International evidence. *International Review of Economics & Finance*, 71, 910–922.
- Wang, J., Sun, T., Liu, B., Cao, Y., & Wang, D. (2018). Financial markets prediction with deep learning. 2018 17th IEEE International Conference on Machine Learning and Applications (ICMLA), 97–104.
- Wang, L. (2005). Support vector machines: theory and applications (Vol. 177). Springer Science & Business Media.
- Xunfa, L. U., LIU, S. K., San LIANG, X., Zhang, Z., & Hairong, C. U. I. (2020). THE BREAK POINT-DEPENDENT CAUSALITY BETWEEN THE CRYPTOCURRENCY AND EMERGING STOCK MARKETS. *Economic Computation & Economic Cybernetics Studies & Research*, 54(4).
- Zeng, T., Yang, M., & Shen, Y. (2020). Fancy Bitcoin and conventional financial assets:

Measuring market integration based on connectedness networks. *Economic Modelling*, 90, 209–220.