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Cryptocurrency Price Prediction using Machine Learning

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Abstract: *Crypto currency has recently received a lot of attention from the media and the public due to its recent price surge and crash. Correspondingly, many researchers have investigated various factors that affect the Crypto currency price and the patterns behind its fluctuations, in particular, using various machine learning methods. In this paper, we study and compare various state-of-the-art deep learning methods such as a Machine Learning (ML), a long short-term memory (LSTM) model, a convolutional neural network, a deep residual network, and their combinations for Crypto currency price prediction. Crypto currency is one of the most popular and valuable crypto currency in the current financial market, attracting traders for investment and thereby opening new research opportunities for researchers. Countless research works have been performed on Crypto currency price prediction with different machine learning prediction algorithms. For the research: relevant features are taken from the dataset having strong correlation with Crypto currency prices and random data chunks are then selected to train and test the model. The random data which has been selected for model training, may cause unfitting outcomes thus reducing the price prediction accuracy. Here, a proper method to train a prediction model is being scrutinised. The proposed methodology is then applied to train a simple Long Short-Term Memory (LSTM) model to predict the crypto currency price for the upcoming 5 days. When the LSTM model is trained with a suitable data chunk, thus identified, sustainable results are found for the prediction. In the end of this paper, the work culminates with future improvements. In addition, a simple profitability analysis showed that classification models were more effective than regression models for algorithmic trading. Overall, the performances of the proposed deep learning-based prediction models were comparable. Connecting Django server to create front end using HTML, CSS, Java Script.*

Keywords: Crypto currency.

I. INTRODUCTION

Machine learning is a very hot topic for many key reasons, and because it provides the ability to automatically obtain deep insights, recognize unknown patterns, and create high performing predictive models from data, all without requiring explicit programming instructions.

This high level understanding is critical if ever involved in a decision-making process surrounding the usage of machine learning, how it can help achieve business and project goals, which machine learning techniques to use, potential pitfalls, and how to interpret the results. The most common machine learning tasks that one may come across while trying to solve a machine learning problem. Under each task are also listed a set of machine learning methods that could be used to resolve these tasks. Please feel free to comment/suggest if I missed mentioning one or more important points.

Following are the key machine learning tasks briefed later in this article:

- Feature selection
- Regression
- Classification
- Clustering
- Density estimation

- Dimension reduction
- Testing and matching

Following are top 8 most common machine learning tasks that one could come across most frequently while solving an advanced analytics problem:

Feature Selection: Feature selection is one of the critical tasks which would be used when building machine learning models. Feature selection is important because selecting right features would not only help build models of higher accuracy but also help achieve objectives related to building simpler models, reduce overfitting etc. The following are some of the techniques which could be used for feature selection:

Filter methods which helps in selecting features based on the outcomes of statistical tests. The following are some of the statistical tests which are used:

- Pearson's correlation
- Linear discriminant analysis (LDA)
- Analysis of Variance (ANOVA)
- Chi-square tests

Wrapper methods which helps in feature selection by using a subset of features and determining the model accuracy. The following are some of the algorithms used:

- Forward selection
- Backward elimination

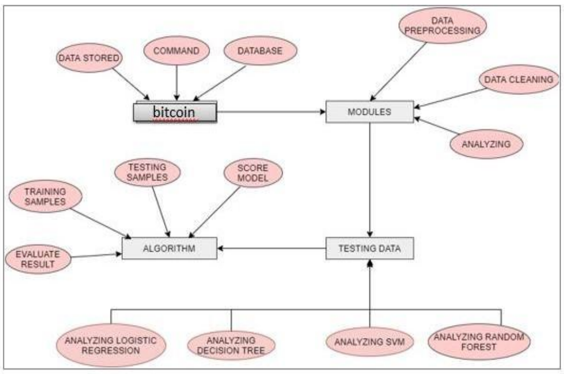
II. EXISTING SYSTEM

The results indicate that Crypto currency's price forecasting in 5-days time window can be achieved with GM (1,1) with average error of 1.14%. To the best of our knowledge, this amount of error is clearly less than previously existed results which have been cited in this article. The autocorrelation plot for 5-days prediction errors is depicted in Fig. 3 which shows that the residuals are uncorrelated in time. Therefore, GM (1,1) can be used to predict Crypto currency price and market trends which leads to reduce the risks of investing in cryptocurrencies. For the future work, one can consider some dependent factors in Crypto currency price and apply GM (1,N) to predict Crypto currency price to get longer period prediction.

III. PROPOSED SYSTEM

Two versions of prediction system will be implemented; one using linear regression and other using Support Vector Machines. The experimental objective will be to compare the forecasting ability of machine learning algorithms. We will test and evaluate both the systems with same test data to find their prediction accuracy. In this project data preprocessing and proposes various deep learning-based prediction models for Crypto currency price regression and classification problems.The first prediction model was based on a Machine Learning. A ML usually consists of an input analysis and then predict the price level.

IV. FLOW DIAGRAM DESIGN



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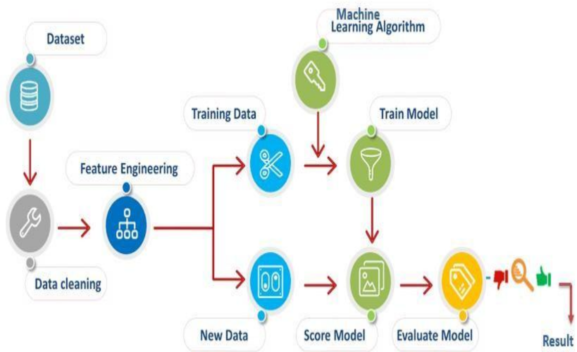
V. ARCHITECTURE DIAGRAM DESIGN



VI. LSTM MODEL DEVELOPMENT MODULE

In this module, The LSTM model is defined to train a neural network that can accurately predict sequential data. the development of the LSTM model involves several steps. Firstly, we preprocess the data by converting the time- series data into a supervised learning problem. This involves transforming the data into input/output pairs, where the input is a window of historical sales data, and the output is the sales value at the next time step. Once the data is preprocessed, we define the LSTM model function using the Keras API. The model architecture includes an input layer, a hidden layer with the ReLU activation function, and an output layer with the sigmoid activation function. We also include dropout regularization to prevent overfitting.

After defining the model function, we compile the model by specifying the optimizer, loss function, and evaluation metric. We use the Adam optimizer, which is a variant of stochastic gradient descent that adapts the learning rate during training. For the loss function, we use mean squared error, which measures the difference between the predicted and actual sales values. We evaluate the model performance using the mean absolute percentage error metric, which measures the percentage difference between the predicted and actual sales values. Once the model is compiled, we fit it to the preprocessed data using the fit() method. During training, the weights of the neural network are adjusted based on the difference between the predicted and actual sales values, in order to improve the model's accuracy. After training, we can use the LSTM model to make predictions on new data. We can input a window of historical sales data into the model, and it will output a predicted sales value for the next time step. The LSTM model can also be used to impute missing values in the time-series data. Overall, the development of the LSTM model in our project involves data preprocessing, model definition, compilation, training, and prediction. By using the LSTM model, we can accurately forecast sales values and make informed business decisions.

VII. LSTM MODEL PREDICTION MODULE

In this module, The LSTM model that was trained on a historical dataset is now used to make predictions on new data. Making predictions using the LSTM model is important because it allows us to use the insights gained from analyzing historical data to predict future outcomes. the trained LSTM model is used to make predictions on new data, which represents future time periods. The input data is preprocessed in the same way as the training data, which involves scaling and reshaping the data to match the input shape expected by the LSTM model. The model is then used to generate predictions for each time step in the future period. The output of the model is a sequence of predicted values, which can be post-processed and analyzed to gain insights into future trends and patterns. Once the predictions have been generated, they can be visualized and analyzed using various techniques, such as time series plots, histograms, and statistical analysis. This allows us to identify patterns and trends in the predicted data, and make informed decisions about future actions. For example, if the predicted sales trends show an increase in demand for a certain product, a business can adjust its marketing and inventory strategies accordingly. Overall, the LSTM model prediction module plays a critical role in leveraging the power of deep learning to generate accurate predictions for future outcomes. This enables businesses and organizations to make more informed decisions, improve efficiency, and mitigate potential risks. This can be useful in a wide range of fields, from finance to healthcare to weather forecasting. By accurately predicting

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future outcomes, we can make more informed decisions and take proactive measures to mitigate potential risks. Businesses can gain valuable insights into future sales trends and make more informed decisions about inventory management, marketing campaigns, and resource allocation.

VIII. FORECAST VISUALIZATION MODULE

The module that visualizes the forecasted data obtained using the LSTM model is responsible for presenting the predictions in a graphical format. This module takes the predicted results from the previous step and creates a plot that shows how the predicted values compare to the actual values over time. Visualizing the predicted results is important because it allows us to see how well our LSTM model performed in forecasting future values. By comparing the predicted values to the actual values, we can assess the accuracy of our model and identify any areas where it may need improvement. The forecast visualization module in our project is designed to provide users with an intuitive and interactive way to explore and analyze the results of our LSTM model's predictions. The module takes the forecasted values generated by the model and displays them in a graphical format, making it easy to visualize how the predicted values compare to the actual values over time. The module uses a popular Python library, Matplotlib, to create visualizations. Matplotlib provides a wide range of tools for creating charts, graphs, and other visualizations, and can be customized to suit the specific needs of our project.

IX. RELATED WORKS

Haya R. Hasan et. al., (2022) Incorporating Registration, Reputation, and Incentivization Into the NFT Ecosystem

A Non-Fungible Tokens (NFTs) have recently received immense popularity in the digital art industry. An NFT represents ownership of a unique item that is stored on the blockchain and cannot be changed, replaced, and copied. The current NFT ecosystem falls short in trust features and is prone to illegitimate users, threats, and vulnerabilities. In this paper, we propose a blockchain- based solution for the NFT ecosystem that incorporates registration of the participating actors, involves a decentralized reputation system, provides incentives to its users through rewards, and penalizes misconduct. Our system design is built to ensure trust and credibility in the NFT ecosystem. The proposed solution leverages blockchain's intrinsic security features such as transparency, tamper-proof logs, data integrity, accountability, and non-repudiation. We use the decentralized storage of the InterPlanetary File System (IPFS) to store the NFTs' metadata, whereas their hash is stored on the chain. We present algorithms along with their implementation, testing, and validation details. We demonstrate how our solution, as well as smart contract code, is secure enough against common security threats and attacks. We make our smart contract code publicly available on the GitHub repository.

Muhammad Muneeb et. al., (2021) SmartCon: A Blockchain-Based Framework for Smart Contracts and Transaction Management.

A smart contract is known to be useful for automating business processes triggered by specific events caused by IoT sensors, data feeds, or other applications. A block chain- based smart contract management system is an innovative technology that is foreseen to automate future business-to- business (B2B) processes. Block chain is well-known to play a central role in business process re-engineering by optimizing business workflow operations, especially in multi-party arrangements. This paper presents a multi-organizational smart contract management system in which a user can create, deploy, and execute smart contracts. This paper consists of two parts; in the first part, we have compared existing smart contract management systems based on different characteristics that can play a vital role in selecting a particular system for a specific business need. In the second part, while utilizing and building upon the state-of-the-art techniques, we have built a framework for a blockchain- based smart contract and transaction management system. It is a unified architecture supporting DAO (Decentralized Autonomous Organizations) and organizational level blockchain-based smart contract execution. There are two types of separate blockchains utilized in the proposed framework, i.e., SBlockchain and TBlockchain. SBlockchain is used to store smart contracts, whereas all the data generated by the smart contracts is stored inside the TBlockchain. In addition, each smart contract has some terms and clauses necessary for some event execution. Various components of the framework and their implementation have been described in detail

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with the help of relevant use-cases.

Satpal Singh Kushwaha et. al., (2022) Ethereum Smart Contract Analysis Tools: A Systematic Review.
Blockchain technology and its applications are gaining popularity day by day. It is a ground-breaking technology that allows users to communicate without the need of a trusted middleman. A smart contract (self-executable code) is deployed on the blockchain and auto executes due to a triggering condition. In a no-trust contracting environment, smart contracts can establish trust among parties. Terms and conditions embedded in smart contracts will be imposed immediately when specified criteria have been fulfilled. Due to this, the malicious assailants have a special interest in smart contracts. Blockchains are immutable means if some transaction is deployed or recorded on the blockchain, it becomes unalterable. Thus, smart contracts must be analyzed to ensure zero security vulnerabilities or flaws before deploying the same on the blockchain because a single vulnerability can lead to the loss of millions. For analyzing the security vulnerabilities of smart contracts, various analysis tools have been developed to create safe and secure smart contracts. This paper presents a systematic review on Ethereum smart contracts analysis tools. Initially, these tools are categorized into static and dynamic analysis tools. Thereafter, different sources code analysis techniques are studied such as taint analysis, symbolic execution, and fuzzing techniques. In total, 86 security analysis tools developed for Ethereum blockchain smart contract are analyzed regardless of tool type and analysis approach. Finally, the paper highlights some challenges and future recommendations in the field of Ethereum smart contracts.

Jiachi Chen et. al., (2020) Defining Smart Contract Defects on Ethereum
Smart contracts are programs running on a blockchain. They are immutable to change, and hence can not be patched for bugs once deployed. Thus it is critical to ensure they are bug- free and well-designed before deployment. A Contract defect is an error, flaw or fault in a smart contract that causes it to produce an incorrect or unexpected result, or to behave in unintended ways. The detection of contract defects is a method to avoid potential bugs and improve the design of existing code. Since smart contracts contain numerous distinctive features, such as the gas system. decentralized , it is important to find smart contract specified defects. To fill this gap, we collected smart-contract-related posts from Ethereum StackExchange, as well as real-world smart contracts. We manually analyzed these posts and contracts; using them to define 20 kinds of contract defects . We categorized them into indicating potential security, availability, performance, maintainability and reusability problems. To validate if practitioners consider these contract as harmful, we created an online survey and received 138 responses from 32 different countries. Feedback showed these contract defects are harmful and removing them would improve the quality and robustness of smart contracts. We manually identified our defined contract defects in 587 real world smart contract and publicly released our dataset. Finally, we summarized 5 impacts caused by contract defects. These help developers better understand the symptoms of the defects and removal priority.

X. FUTURE GOALS

Regularity slant and arbitrariness and future estimates will offer assistance to analyze deal drops which the companies can maintain a strategic distance from by employing a more focused and efficient strategies to play down the deal drop and maximize the benefit and stay in competition. The exactness of the expectation can be improved in future so that the recognizable proof of deals can be found on the leading. There are several potential areas of improvement for this project. One goal could be to expand the scope of the analysis by using more data sources and incorporating additional variables such as news sentiment or market trends. Another goal could be to optimize the hyperparameters of the LSTM model to improve its accuracy and performance. Additionally, the project could be extended to other industries or asset classes beyond just stocks. Overall, there is ample room for further development and exploration in this area of financial forecasting using machine learning techniques. Expanding the scope of the analysis involves exploring different industries and asset classes beyond stocks. For example, the techniques and models developed for sales forecasting in the retail industry can be applied to other industries such as healthcare, energy, or transportation. Additionally, the models can be applied to other types of time series data such as exchange rates, commodity prices, or weather data. Furthermore, we can also focus on creating a user-friendly interface for the proposed system so that businesses can easily input their data and obtain accurate sales forecasts. Additionally, we can develop a recommendation engine that suggests strategies to maximize profit and minimize sales drops based on the predicted sales trends. Overall, the future goals of this project involve improving the accuracy of sales forecasts and expanding the scope of the analysis while also providing a user-friendly interface for businesses to obtain insights and make informed decisions.

XI. CONCLUSION

Conclusions All in all, predicting a price-related variable is difficult given the multitude of forces impacting the market. Add to that, the fact that prices are by a large extent depended on future prospect rather than historic data. However, using deep neural networks, has provided us with a better understanding of Crypto currency, and LSTM architecture. The work in progress, includes implementing hyperparameter tuning, in order to get a more accurate network architecture. Also, other features can be considered (although from our experiments with Crypto currency, more features have not always led to better results). Microeconomic factors might be included in the model for a better predictive result.

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