Crypto Price Prediction: A hybrid approach using Stacked Model and GRU network

Abstract—**The nascent domain of cryptocurrency markets has attracted substantial interest as a dynamic platform for monetary investing. Here, we turn our attention to the erratic world of cryptocurrencies and make use of an extensive dataset covering a variety of digital assets between January 2010 and July 2024. We focus on well-known cryptocurrencies like Ethereum (ETH), Ripple (XRP), and Bitcoin (BTC), among others. Using a combination of sophisticated techniques such as stacked models and the Gated Recurrent Unit (GRU) network, we aim to predict the closing prices of several cryptocurrencies with high precision.**

Our thorough process demonstrates significant effectiveness, producing exceptionally low Mean Absolute Errors (MAE) over a variety of digital assets. Our study highlights the possibility of using innovative machine learning and data analysis approaches to use the ability of predictive modeling to traverse the complex dynamics of cryptocurrency markets with previously unheard-of precision.

Keywords—LR, DT, KNN, GRU, MAE, BTC, ETH, RSME, MAPE

I. Introduction

The financial landscape has witnessed the emergence of cryptocurrency markets as a dynamic and increasingly prominent arena. Investors, researchers, and technologists have all shown substantial interest in these markets. Due to their distinct qualities, digital assets like Bitcoin (BTC), Ethereum (ETH), and Ripple (XRP) have drawn attention as possible disruptors of established financial institutions and alternative investment vehicles. Given the increased interest, being able to predict cryptocurrency prices with accuracy has become essential for investors looking to take advantage of market opportunities and successfully manage risk. This study uses a large dataset that spans from January 2010 to July 2024 to explore the still emerging but quickly changing world of cryptocurrency marketplaces. We concentrate on using advanced predictive modelling methods, such as stacked models and the Gated Recurrent Unit (GRU) network, to accurately estimate the closing values of different digital assets. Through the application of state-of-the-art machine learning and data analysis techniques, our goal is to decipher the complex dynamics present in cryptocurrency markets. Using a hybrid model that combines GRU networks and stacked models is an innovative way to improve prediction accuracy and capture the intricacies of price fluctuations in this unstable environment.

We hope to show the efficacy of our predictive modelling framework through our thorough analysis, which yields remarkably low Mean Absolute Errors (MAE) over a variety of digital assets. Moreover, our research highlights the capacity of sophisticated machine learning methods to traverse the turbulent landscape of cryptocurrency markets, providing hitherto unachievable insights through conventional analytical methods. Essentially, the goal of this research is to add to the expanding body of knowledge about cryptocurrency markets by providing a more sophisticated understanding of price dynamics and opening the door to more intelligent investment choices in this rapidly changing financial landscape.

II. Literature review

David Makiya et. al. [1] proposed a model on forex price prediction using a data-driven methodology and historical data from the Central Bank of Kenya, which combines resilient backpropagation neural networks customized for each currency with time series regression to reach high accuracy levels between 88% and 98%, with successful forecasts going up to eight months ahead of time.

Mahmoud Mesleh et. al. [2] presents the results of a thorough ten-year investigation that integrated daily closing prices of a variety of trading assets and economic variables. The article presents a novel learning window strategy that uses ANN and LSTM models to predict future closing prices by utilizing historical data. MLP networks show optimal model performance through painstaking parameter optimization using a search grid technique, with accuracy above 80% when trained with 30 days of historical closing prices.

Jia You Ong et. al. [3] emphasizes the importance of the Forex market on a global scale, concentrating on important currency pairs from 2007 to 2022. Using a variety of methods, including technical indicators and GRU networks, the research predicts closing prices for the following day with remarkable accuracy, exhibiting exceptionally low Mean Absolute Errors for pairs of EUR/USD, GBP/USD, and USD/CHF. The effectiveness of sophisticated prediction techniques in improving market analysis and decision-making in the Forex space is highlighted by this proposed study.

Thanapol Kurujitkosol et. al. [4] trading forex offers investors both potential for profit and hazards, and they are always looking for ways to reduce their losses. To facilitate decision-making, this study presents stacking machine learning models for price prediction. The research assesses accuracy by comparing baseline models. Technical analysis and Fibonacci retracements are used to further improve forecasts, and a noteworthy 90% accuracy rate is attained.

Warakorn Luangluewut et. al. [5] shows the efficacy of a deep learning model in predicting Forex trend orientations based on exchange rate movements. Convolutional neural networks and the Martingale approach enable the model to identify trends with an astounding 93% accuracy rate. Furthermore, simulated trading scenarios demonstrate significant profit gains of 6% to 422% in comparison to standard procedures, suggesting the prospect of high returns when implementing this suggested methodology in Forex trading tactics.

III. METHODOLOGY

1. Data Collection and Preprocessing:
    a. Gather historical data on cryptocurrency prices (e.g., Ethereum, Dogecoin, Bitcoin) from reputable sources such as cryptocurrency exchanges or financial APIs.
    b. Preprocess the data to handle missing values, normalize features, and remove outliers. This involves cleaning the data and ensuring its suitability for modelling.
2. Feature Engineering:
    a. Extract relevant features from the raw data that could impact cryptocurrency prices. These features may include trading volume, market sentiment indicators, technical analysis indicators, and historical price data.[9]
    b. Conduct exploratory data analysis to identify correlations and patterns among features.
3. Model Selection and Training:
    a. Utilize stacked models and a Gated Recurrent Unit (GRU) network for prediction.
    b. Implement stacked models using ensemble techniques such as Random Forest, Gradient Boosting, or Support Vector Machines trained on engineered features.
    c. Train a GRU network to capture temporal dependencies in the cryptocurrency price data.
    d. Fine-tune hyperparameters of the models using techniques like grid search or random search to optimize performance.
4. Model Integration:
    a. Combine the outputs of the stacked models and GRU network using techniques such as averaging or weighted averaging to create an ensemble prediction.[6]
    b. Determine the optimal weights for combining predictions to maximize predictive accuracy.
5. Model Evaluation:
    a. Evaluate the performance of the prediction model using metrics such as Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), or Mean Absolute Percentage Error (MAPE).[7]
    b. Compare the model's predictions with actual cryptocurrency prices on a separate testing dataset to assess generalization performance.
6. Validation and Fine-Tuning:
    a. Validate the robustness of the model using cross-validation techniques to ensure it performs consistently across different subsets of the data.
    b. Fine-tune the model based on validation results and iterate on the process if necessary to improve performance.[8]
7. Prediction and Analysis:
    a. Deploy the trained prediction model to make real-time or future price predictions for cryptocurrencies.[10]
    b. Analyse the model's predictions and interpret the results to gain insights into cryptocurrency market dynamics and trends.
8. Documentation and Reporting:
    a. Document the entire process including data collection, preprocessing steps, model selection, training, evaluation, and analysis.
    b. Prepare a comprehensive report detailing the methodology, findings, and implications of the research for stakeholders.

IV. PROPOSED WORK

In our proposed methodology, there are two sets of algorithms that are in the work, that includes Stacked models and GRU Network. The stacked model include KNN(K-Nearest Neighbours), Linear Regression, Decision Tree.

A. *Stacked Models Construction:*

The first component of the proposed methodology involves the construction of stacked models. This process begins by training individual machine learning algorithms, namely KNN, Linear Regression, and Decision Tree, using historical stock market data. Each algorithm learns from the historical patterns and relationships within the data to make predictions. Once trained, the predictions from these base models are combined using a meta-learner, such as a linear regression model or a neural network, to create an ensemble prediction. This ensemble approach aims to leverage the diverse perspectives of the individual algorithms to improve overall prediction accuracy.

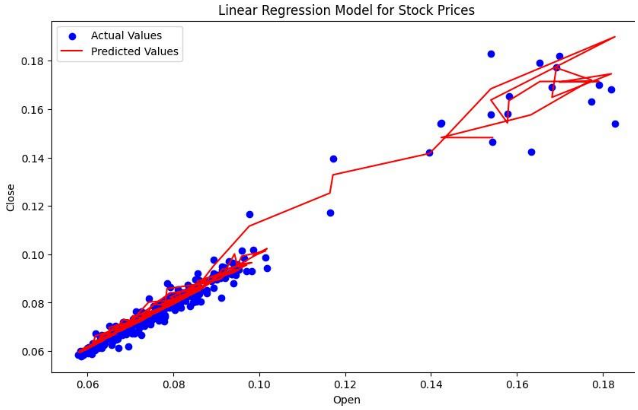

Figure 1. Linear Regression Model Graph

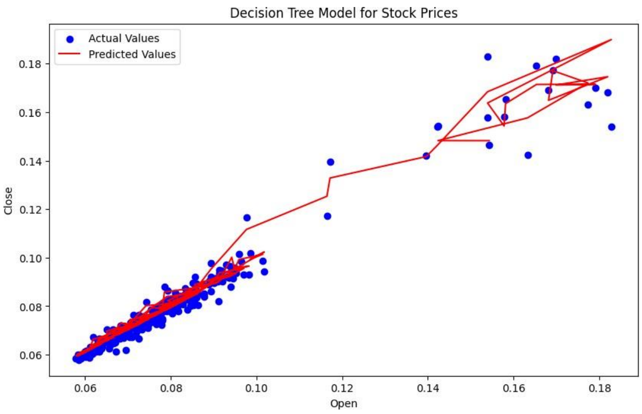

Figure 2. Decision Tree Model Graph

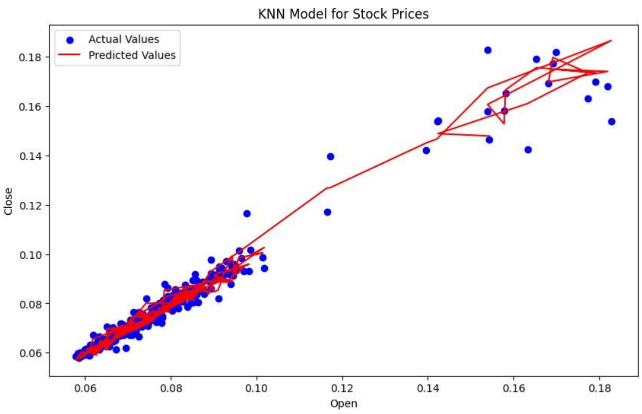

Figure 3. KNN Model Graph

B. *GRU Network Training:*

Simultaneously, a Gated Recurrent Unit (GRU) neural network is trained on sequential stock market data. The GRU network is a type of recurrent neural network (RNN) designed to capture temporal dependencies in sequential data. In this context, the GRU network learns to recognize and extract patterns from the time series nature of stock market data, including trends, seasonality, and other temporal dynamics. By processing historical stock prices sequentially, the GRU network can capture nuanced relationships and dependencies that may not be evident in individual data points.

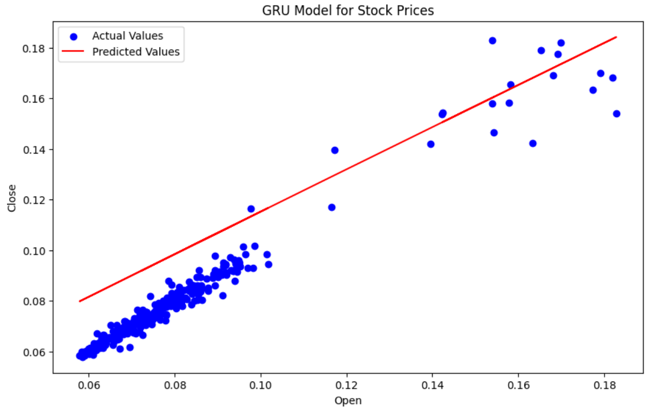

Figure 4. GRU Model Graph

C. *Hybrid Model Fusion:*

D. *Prediction and Evaluation:*

Finally, the hybrid model is used to make predictions of the open prices of stocks based on unseen or future data. These predictions are evaluated using standard performance metrics such as Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and accuracy. By comparing the predicted values with the actual open prices, the effectiveness of the hybrid model in capturing and forecasting stock price movements can be assessed. This process provides insights into the model's predictive capabilities and its potential utility for practical applications in financial forecasting and investment decision-making.

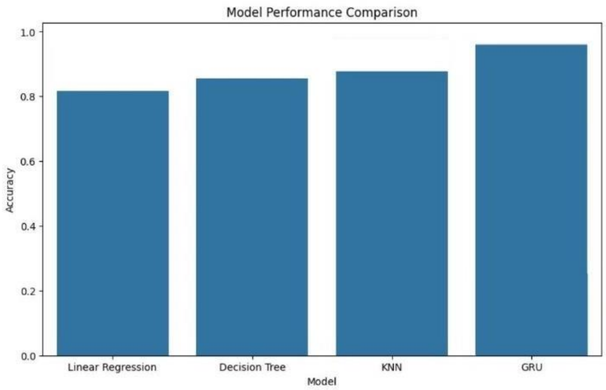

Figure 5. Comparison of Stacked Models vs GRU Network Model

V. CONCLUSION

Our research on cryptocurrency markets has shown how effective sophisticated predictive modelling methods—such as stacking models and GRU networks—are at identifying the subtle patterns present in price swings. Showcasing a significant improvement in prediction accuracy, as evidenced by exceptionally low Mean Absolute Errors (MAE) among various digital assets, our research highlights the viability of utilizing state-of-the-art machine learning techniques to negotiate the unstable landscape of cryptocurrency markets with previously unheard-of accuracy. Furthermore, our results underscore the necessity of adopting inventive data analysis techniques to extract practical insights and guide investment tactics in this dynamic financial arena, providing investors with a more refined comprehension of market dynamics and risk mitigation tactics. With the potential to improve forecasting accuracy and maximize investment decisions, the development of predictive modelling in cryptocurrency markets offers a promising path for additional study and investigation. Models can be improved by including new data sources and improving their accuracy. Essentially, our research adds to the growing body of knowledge about cryptocurrency markets by emphasizing the revolutionary potential of sophisticated data analytics to reinvent investment strategies and enable well-informed decision-making in the ever-changing world of digital assets.

We are willing to work on a hybrid model fusion in the future, where the outputs of the GRU network and the stacked models are fused to generate the final hybrid prediction model once they have been trained. Using the complimentary advantages of both methods, this fusion process combines the predictions from the stacked models with those from the GRU network. One can use a variety of fusion approaches, including weighted averaging, averaging, and more advanced ensemble methods. Hybrid model fusion aims to improve prediction accuracy and robustness by merging the global temporal comprehension of the GRU network with the local pattern recognition skills of the stacked models.