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Cryptocurrency Forecasting: A Comparative Study of Machine Learning and Deep Learning Approaches

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Summary

In today's financial landscape, understanding and predicting cryptocurrency trends are of utmost importance due to the significant growth of digital currencies. This paper delves into a comprehensive study of predictive modeling for six major cryptocurrencies: Bitcoin, Dogecoin, Ethereum, USDCoin, BinanceCoin, and Cardanocoin. Using a wide range of machine learning and deep learning algorithms, we carefully assess how well each model can capture the complex nature of cryptocurrency markets. We employed a rigorous methodology, including models like Long Short-Term Memory (LSTM), Convolutional Neural Networks (CNN), Support Vector Machines (SVM), and eXtreme Gradient Boosting (XGBoost), among others. We evaluated each model's performance using standard metrics like RMSE and R^2. The results show that different models perform differently, with some algorithms excelling in predicting specific cryptocurrencies.

***Index Terms*—Cryptocurrencies, Machine Learning, Deep Learning, Bitcoin, Dogecoin, Ethereum, USDCoin, BinanceCoin, Cardanocoin.**

I. Introduction

The evolution of the financial landscape into the digital realm is significantly marked by the rapid emergence of cryptocurrencies.

These have, within a short time frame, exerted transformative impacts on the global economy [1]. A notable figure in this digital transformation is Bitcoin. As a trailblazing entity, Bitcoin has not only initiated a financial paradigm shift but also paved the way for numerous other cryptocurrencies aspiring to emulate or exceed its accomplish- ments [2]. As these digital currencies increasingly become in- tegrated into various financial transaction strata, their potential profitability and relevance have elevated them to a central position in contemporary financial dialogues. However, the unpredictable nature of the cryptocurrency market, especially in terms of its volatility, renders predicting their price trends a daunting task [3]–[5]. This complexity in predicting the rapid shifts in cryptocurrency values is reminiscent of challenging tasks from ancient myths. In light of this challenge, our research aims to provide a detailed study of predictive models for five major cryptocurrencies: Bitcoin, Dogecoin, Ethereum (ETH), USDCoin, BinanceCoin, and Cardanocoin.

In our research journey, we employ both conventional machine learning (ML) and modern deep learning (DL) tech- niques. Our empirical analysis covers an extensive set of models, including Long Short-Term Memory (LSTM) net- works [6], Convolutional Neural Networks

(CNN) [7], Support Vector Machines (SVM) [8], K-Nearest Neighbors (KNN) [9], eXtreme Gradient Boosting (XGBoost) , the linear model from Astro ML, as well as traditional regression approaches like LASSO [10], RIDGE [11], and Linear Regression (LR) [12]. We also integrate DT Regressors and Gaussian Process (GP) Regressors to ensure a holistic approach.

We rigorously assess each model using the Root Mean Square Error (RMSE) and the R-squared (R^2) metric to determine their prediction accuracy and efficacy. Given the distinct characteristics of each digital currency, our mul-tifaceted methodology, which spans from DL models that recognize time-related patterns to conventional models like SVM and XGBoost, offers predictions that consider each cryptocurrency's unique attributes.

Combining various methodologies not only upholds rig- orous academic standards but also provides a platform for innovative insights. As we navigate the juncture between traditional and digital finance, our research, encapsulated in this paper, aims to serve as a guide, highlighting efficient predictive techniques. We aspire that this amalgamation of ML and DL models aids stakeholders, investors, and scholars in gaining a profound comprehension of the cryptocurrency prediction landscape, thereby facilitating informed decision- making and stimulating further academic inquiry in this con- tinuously adapting field.

In the subsequent sections of this paper, we systematically present our findings and discussions. We begin with the *Related Works* section, which reviews pertinent literature to establish a foundational understanding and context. Following this, the *Methodology* section elucidates the specific tools, techniques, and processes we employed in our research. We then present our empirical findings in the *Results* section, sup- ported by appropriate data visualizations and tables. Finally, the *Conclusion* section synthesizes our primary takeaways, insights, and the broader implications of our study, while also suggesting potential directions for future research in this domain.

II. Related Works

The subsequent section provides an overview of pivotal research and studies conducted in the realm of cryptocur- rency forecasting, underscoring the methodologies employed and insights gained. These studies collectively showcase the advancements in the application of machine learning, deep learning, and various hybrid models in understanding and predicting cryptocurrency market behaviors.

Paper [13] explores the world of cryptocurrencies and their rising significance in financial transactions. Given their volatility, there's an emphasis on reliable forecasting models. This research introduces a multiple-input deep neural network for predicting cryptocurrency trends. By processing individual cryptocurrency data, the model extracts specific insights. Tests on Bitcoin, Ethereum, and Ripple over three years reveal that this model efficiently uses mixed data, minimizes overfitting, and is computationally superior to standard deep neural net- works.

Research [14] investigates predictive capabilities for Bit- coin, Ethereum, and Litecoin using ML methods such as linear models, random forests, and SVMs. The objective is to gauge these models' efficacy during market fluctuations. Using data from August 15, 2015, to March 03, 2019, these models were trained and tested. Fewer than one-third of the tested models had below 50% success. A standout model, ”Ensemble 5”, showed high performance for Ethereum and Litecoin, factoring in trading costs. The conclusion emphasized ML's potential for cryptocurrency predictions and strategy development.

Research [15] highlights the growing role of cryptocurrency in finance, recognizing both its potential and volatility. With fluctuating cryptocurrency values, there's a need for advanced forecasting models. This study innovatively combines en- semble learning techniques with deep learning models to predict hourly cryptocurrency prices. It integrates advanced models like LSTM and Bi-directional LSTM. These models predict upcoming hourly prices and their relative movement (up/down). To verify these models, the research evaluates prediction error autocorrelation, emphasizing the synergy be- tween ensemble learning and deep learning in building reliable predictors.

Paper [16] delves into the unpredictable realm of cryp- tocurrencies like Ethereum and XRP, emphasizing their de- centralized, third-party intervention-free operation. With the volatility seen in these digital currencies paralleling traditional stock markets, accurate forecasting has garnered interest. The study introduces an LSTM-based forecasting model tailored for AMP, Ethereum, Electro-Optical System, and XRP. Perfor- mance evaluation metrics include MSE, RMSE, and NRMSE. The findings underscore LSTM's superior predictive capabil- ities for all examined cryptocurrencies. Specifically, for XRP, the model achieved correlation values of 96.73% in training and 96.09% in testing. When compared to other systems, the LSTM model emerged as remarkably accurate, underscoring its relevance in the cryptocurrency sector.

Study [17] employs DL techniques to forecast the prices of major cryptocurrencies: Bitcoin, Digital Cash, and Ripple. This represents an innovative application of DL in cryp- tocurrency prediction. The initial analysis indicates that these cryptocurrencies' time series data exhibit fractal behaviors and extended memory. Comparing the predictive capacities of LSTM networks with the generalized regression neural model reveals LSTM's superior accuracy. The generalized regression model struggles with capturing overarching non- linear patterns, especially in noisy data, due to its Gaussian kernel reliance. While LSTM demands greater computational power, its capability in interpreting the complex tendencies of cryptocurrency markets positions it as the preferred model for such predictions.

Study [18] explores Bitcoin price predictions using a deep forward neural network (DFFNN). The research ex- amines the impact of different numerical training algo- rithms on DFFNN's forecasting accuracy. Of the three algo- rithms tested—conjugate gradient with Powell-Beale restarts, the resilient algorithm, and the Levenberg-Marquardt algo- rithm—the latter showcased the highest accuracy based on RMSE values. The resilient algorithm, although less precise, demonstrated faster processing, which may be valuable for real-time operations. In essence, the DFFNN paired with the Levenberg-Marquardt algorithm emerged as a robust tool for Bitcoin price predictions.

Paper [19] underscores blockchain technology's growing relevance, emphasizing cryptocurrencies such as Litecoin and Zcash. Addressing the volatility of the crypto market, the study presents a hybrid model, merging Gated Recurrent Units (GRU) and Long Short Term Memory (LSTM), aimed at predicting cryptocurrency prices while factoring in parent coin influences. The proposed model outperformed existing models in accuracy during tests, marking its potential for real-time cryptocurrency market analysis.

Research [20] highlights Business Intelligence's role in aid- ing managerial decisions, especially in the volatile cryptocur- rency market. Recognizing market sensitivity to global occur- rences, the study introduces a model to forecast prices of five major cryptocurrencies, leveraging DL, LR, and support vector regression (SVR) techniques. These methods are enhanced with sentiment data from significant global events. Results point to the dominance of DL and SVR in forecasting, with accuracy significantly bolstered when incorporating sentiment data, particularly when combining sentiments from various events.

Paper [21] delves into cryptocurrencies and their crypto- graphic security features like SHA-2 and MD5. Given the growing interest in these digital assets and their price volatility, forecasting their values is crucial. Various ML and DL tech- niques have been adopted to predict these prices. The research introduces a hybrid prediction model, blending LSTM and GRU, with a focus on Litecoin and Monero. The outcomes suggest that this model is highly accurate in predicting cryp- tocurrency prices, hinting at its broader applicability across various cryptocurrencies.

Research [22] investigates short-term cryptocurrency fore- casting using ML methods, centering on Bitcoin, Ethereum, and Ripple over 90 days. Using the Binary Autoregressive Tree (BART) model, Multilayer Perceptron (MLP), and Random Forest (RF), the models were advantageous as they forecasted using only past data values without stringent conditions. In comparisons, all showed promising results, with BART and MLP averaging a 3.5% mean absolute percentage error (MAPE), and RF around 5%. Additionally, BART was em- ployed to predict price direction for trading using a binary classification, underscoring ML’s potential in short-term pre- dictions and its implication for online trading algorithms.

Research [23] delves into predicting Bitcoin, Litecoin, and Ethereum prices through three recurrent neural network (RNN)

models. The Gated Recurrent Unit (GRU) emerged as the most accurate for all cryptocurrencies, with MAPE values of 0.2454% for BTC, 0.8267% for ETH, and 0.2116% for LTC.
In comparison, the bidirectional LSTM (bi-LSTM) performed least effectively among the tested algorithms. Such predictive tools are essential for aiding investment decisions in the cryptocurrency arena. The conclusion points to potential future studies incorporating influencers like social media, tweets, and trading volumes to better understand cryptocurrency price determinants.

III. METHODOLOGY

In the method part of our study, we outline a clear four-step process to handle the complex challenges of cryptocurrency price prediction. As illustrated in Figure 1, or first step is a detailed data collection step, collecting details from six impor- tant datasets for major cryptocurrencies: Bitcoin, Dogecoin, Ethereum, USDCoin, Binance Coin, and Cardano Coin. This collected data is the base for the next steps of our study. After collecting the data, we move to cleaning it up, a step where we remove any missing information to make the data reliable, adjust it using the MinMaxScaler to fit a certain scale, and split the dataset into training and testing parts to keep a balance. Once the data is ready, we move to the modeling step, using modern tools to find patterns in the data. Our method ends with a testing step, where we carefully check how well our models work. We want to make sure our predictions are strong and show the real trends in the cryptocurrency market. Our organized four-step method shows our detailed approach and places our study as a key piece in the field of cryptocurrency study.

A. Data collection

In our study, we focused on datasets retrieved from kaggle website [24] from six prominent cryptocurrencies based on their historical pricing records. We concentrated on Bitcoin, Dogecoin, Ethereum, USDCoin, Binance, and Cardano, with their respective trading symbols presented in Table I.

TABLE I
CRYPTOCURRENCY TRADING SYMBOLS

Cryptocurrency	Symbol
Bitcoin	BTC
Dogecoin	DOGE
Ethereum	ETH
USDCoin	USDC
Binance Coin	BNB
Cardano Coin	ADA

The dataset incorporates seven principal attributes, which include:

- **date**: Represents the specific date of the cryptocurrency price.
- **open**: Denotes the starting price at the beginning of the day.
- **high**: Marks the highest price reached during the day.
- **low**: Indicates the lowest price achieved on that day.
- **close**: Refers to the final price at the end of the day.
- **adj close**: Gives an average price for the day.
- **volume**: Shows the total number of cryptocurrency trans- actions for the day.

B. Data preprocessing

In our study, preprocessing emerged as a foundational step, ensuring the quality and consistency required for further analyses. We prioritized establishing a clean and normalized foundation from our datasets—Bitcoin, Dogecoin, Ethereum, USDCoin, Binance Coin, and Cardano Coin. Our first fo- cus was on identifying and eliminating missing values to maintain the reliability of our models. Following this, we embarked on data normalization, ensuring consistency across varied datasets. We employed the *MinMaxScaler* for this task, transforming our data to fall within a 0 to 1 range. This not only avoids feature dominance due to scale discrepancies but also readies the data for effective ML algorithm application. Concluding the preprocessing, we split our data into training (70%) and testing (30%) subsets, in line with established ML best practices. This ensured a substantial dataset for model training and a separate set for unbiased evaluation. Our meticulous preprocessing prepares our data optimally for detailed modeling and evaluation.

C. Modeling

In our research, modeling played a central role, transforming our refined datasets into meaningful insights using predictive algorithms. We utilized a diverse set of models, each chosen for their unique strengths in predicting cryptocurrency closing prices:

- **LSTM (Long Short-Term Memory)**: A type of RNN adept at capturing long-term patterns in sequential data. Our LSTM model uses multiple layers with dropouts and a sigmoid activation function [25].
- **CNN (Convolutional Neural Network)**: Recognized for image processing, its ability to detect time series patterns is leveraged here. Our architecture uses convolutional, max-pooling, dropout, and dense layers [26].
- **SVM (Support Vector Machines)**: An algorithm renowned for finding optimal separation in high- dimensional space [27].
- **KNN (K-Nearest Neighbors)**: Predicts output using the ’k’ closest training data points [28].
- **XGBoost**: A gradient boosting algorithm that constructs and refines decision trees [29].
- **Linear Model (Astro ML)**: Tailored for large datasets, drawing from astrophysical applications [30].
- **LASSO**: Employs shrinkage for feature selection [31].
- **RIDGE**: Counters multicollinearity by introducing bias [32].
- **Linear Regression**: Establishes linear relationships, serv- ing as a model benchmark [33].
- **Decision Tree Regressor**: Captures non-linear patterns, segmenting data for precise predictions [34].
- **Gaussian Process Regressor**: Adaptable to various data patterns due to its non-parametric nature [35].

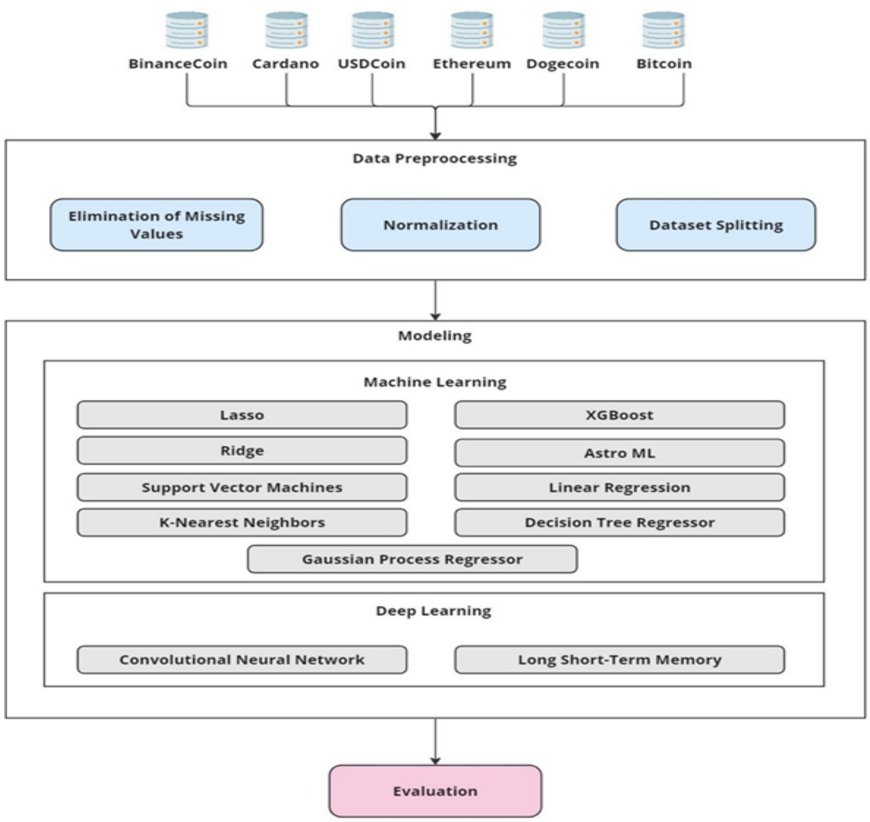

Fig. 1. Proposed approach

By incorporating this diverse suite of algorithms, we aimed to comprehensively analyze and forecast the dynamics of cryptocurrency prices.

IV. Results

Table II presents a comprehensive comparative analysis of the performance of twelve machine learning models on six cryptocurrency datasets, namely Bitcoin, Dogecoin, Ethereum, USDcoin, Binance Coin, and Cardano. The table provides a detailed evaluation of the predictive capabilities of each model on each dataset, reporting two key performance metrics: Root Mean Squared Error (RMSE) and R-squared (R2). The results shown in the table reveal notable differences in the performance of the models across the various cryptocurrency datasets. The LSTM model achieves excellent predictive ac- curacy on the Bitcoin dataset, with an RMSE value of 0.020 and an R2 value of 0.994, indicating a strong predictive relationship. In contrast, the SVM model performs poorly on the Bitcoin dataset, with an RMSE value of 0.358 and an R2 value of 0.614, indicating limited predictive capabilities. The XGBoost model exhibits consistent performance across most datasets, with RMSE values ranging from 0.076 to 0.376 and R2 values ranging from 0.040 to 0.760, demonstrating its robustness and versatility. The LASSO model performs well on the Ethereum dataset, with an RMSE value of 0.333 and an R2 value of 0.647, indicating effective feature selection

and predictive capabilities. Overall, the results presented in Table II provide valuable insights into the strengths and weak- nesses of various machine learning models for cryptocurrency price prediction. The LSTM and XGBoost models generally outperform other models in terms of RMSE and R2 values, indicating their suitability for cryptocurrency price prediction tasks. In contrast, the SVM and DT models exhibit poor performance on most datasets, suggesting limitations in their predictive capabilities. The GP model performs inconsistently across datasets, indicating potential issues with hyperparam- eter tuning or model specification. These findings facilitate informed decisions about model selection and optimization for practical applications.

V. Conclusion

In the dynamic world of cryptocurrencies, this study offers an in-depth analysis of six key digital currencies using various predictive models. We observed varying predictive capacities across models, emphasizing the necessity for customized approaches based on the cryptocurrency in question. The results also highlighted that apart from quantitative meth- ods, understanding real-world events and market sentiments is crucial in predicting cryptocurrency behaviors. For future research, incorporating advanced deep learning models, inte- grating emerging cryptocurrencies, and utilizing real-time data like news sentiments can further enhance prediction accuracy.

TABLE II
COMBINED CRYPTOCURRENCY MODEL RESULTS

Model	Bitcoin		Dogecoin		Ethereum		USDcoin		Binance Coin		Cardano	
	RMSE	R2	RMSE	R2	RMSE	R2	RMSE	R2	RMSE	R2	RMSE	R2
LSTM	0.2357	0.3	0.224606	0.321	0.164	0.599	0.013	0.017	0.242	0.269	0.042	0.973
CNN	0.319	0.286	0.102923	0.772	0.094	0.867	0.013	0.017	0.242	0.269	0.067	0.932
SVM	0.358	0.614	0.221495	0.285	0.0267	0.059	0.036	7.234	0.393	0.924	0.358	0.024
KNN	0.311	0.223	0.221376	0.283	0.219	0.287	0.015	0.495	0.380	0.798	0.233	0.204
XGBoost	0.076	0.040	0.217567	0.240	0.174	0.547	0.014	0.245	0.376	0.760	0.186	0.491
Astro ML	0.276	0.040	0.226077	0.338	0.267	0.060	0.024	2.593	0.397	0.958	0.296	0.291
LASSO	0.420	1.226	0.226155	0.339	0.333	0.647	0.032	5.350	0.399	0.979	0.363	0.941
RIDGE	0.036	0.983	0.192560	0.028	0.0398	0.976	0.014	0.237	0.159	0.685	0.049	0.964
LR	0.020	0.994	0.032685	0.972	0.022	0.992	0.014	0.350	0.032	0.9887	0.030	0.986
DT	0.322	0.306	0.220465	0.273	0.20	0.403	0.020	1.419	0.377	0.798	0.220	0.290
GP	0.020	0.994	0.031669	0.973	0.022	0.992	0.014	0.326	0.032	0.987	0.030	0.986

There's also potential to study other significant metrics, like transaction volume or market capitalization, in addition to price forecasts. This work serves as a starting point with abundant avenues for further exploration in cryptocurrency forecasting.

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