Bitcoin Price Direction Prediction Using Machine Learning and Deep Learning Techniques

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***Abstract*—This study investigates the performance of different machine learning (ML) and deep learning (DL) models in predicting Bitcoin's hourly price movement direction. Using a comprehensive dataset including historical cryptocurrency prices, trading volumes, sentiment indicators, and economic indices, we performed an end-to-end machine learning pipeline covering preprocessing, feature selection, model training, evaluation, and analysis. Among the tested models, Convolutional Neural Network (CNN) achieved the highest accuracy at 51.56%, although it suffered from class imbalance by predicting only the positive class. These findings reveal the complexity of financial time-series classification tasks and highlight the necessity of advanced feature engineering and robust evaluation techniques for achieving reliable predictions. Additionally, our research sheds light on the challenges of modeling highly volatile markets and emphasizes the importance of incorporating multiple data sources for enhancing predictive power.**

***Index Terms*—Bitcoin, Machine Learning, Deep Learning, Financial Forecasting, Time Series, Feature Selection, Cryptocurrency, Financial Data Analysis**

I. Introduction

Cryptocurrencies have gained significant attention in recent years due to their decentralized nature and highly volatile market dynamics. Bitcoin, being the most dominant cryptocurrency, attracts both individual and institutional investors seeking profitable trading opportunities. Predicting the future price direction of Bitcoin is of paramount importance for algorithmic trading, risk management, and investment decision-making. However, the task is challenging because of the market's susceptibility to external influences such as regulatory changes, social media sentiment, and global economic events.

This research focuses on predicting whether Bitcoin's price will increase in the next hour, formulating the problem as a binary classification task. We employed a comparative approach by utilizing a diverse set of machine learning (ML) and deep learning (DL) models. The study not only evaluates the performance of these models but also examines the impact of feature selection techniques on predictive accuracy. By integrating both traditional and modern approaches, this paper aims to contribute insights into the potential and limitations of predictive modeling in cryptocurrency markets.

It is worth noting that cryptocurrency markets operate 24/7, unlike traditional stock markets. Therefore, the temporal features extracted from the dataset, such as hour of the day and day of the week, may exhibit unique patterns that differ from traditional financial markets. This characteristic adds an extra layer of complexity to the prediction task and highlights the necessity of tailored feature engineering strategies for this domain.

II. Dataset Description

The dataset used in this study is sourced from Kaggle under the name "Bitcoin Pulse Market Trends and Fear Dataset." It comprises 17,515 hourly records collected over a period encompassing various market conditions. Each record includes 131 features such as open, high, low, close (OHLC) prices, traded volume, and several external indicators like Google Trends data, VIX index values, and major global stock indices.

A unique aspect of this dataset is its inclusion of non-crypto financial indices, allowing us to explore the correlation between Bitcoin movements and traditional markets. The presence of both market-specific and macroeconomic features offers an opportunity to investigate multidimensional relationships influencing Bitcoin price behavior.

TABLE I
Dataset Overview

Property	Value
Number of Records	17,515
Number of Features	131
Missing Values	None
Non-numeric Columns	Datetime only
Target Variables	target_class, target_reg

The dataset did not contain missing values, eliminating the need for imputation. The only non-numeric column, `Datetime`, was processed separately to extract meaningful temporal features. Additionally, data exploration revealed that some features had constant values across all records; these were removed to improve computational efficiency and reduce redundancy in the model input.

III. Preprocessing and Feature Engineering

The raw `Datetime` field was decomposed into categorical variables including `hour`, `month`, and `day_of_week` to capture temporal patterns that may influence price movements. Label Encoding and One-Hot Encoding were applied to these categorical features to ensure compatibility with machine learning algorithms. Fig. 1, Fig. 2, and Fig. 3 show the distribution of these features.

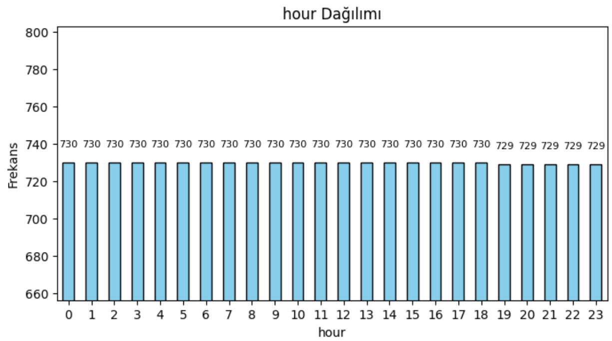

Fig. 1. Hour Feature Distribution

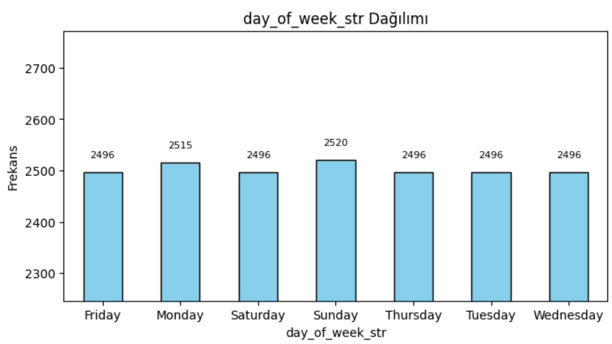

Fig. 2. Day of Week Feature Distribution

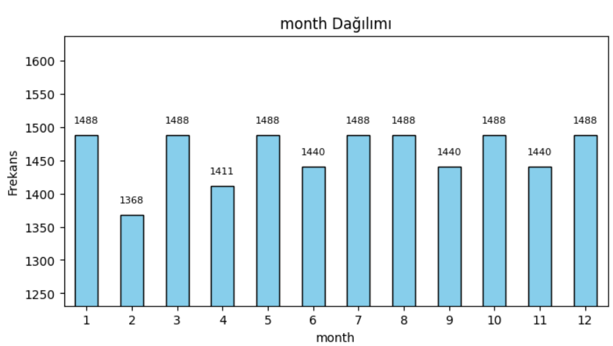

Fig. 3. Month Feature Distribution

Constant features were identified and removed to reduce dimensionality and avoid redundant information. All numerical features were normalized using MinMaxScaler to ensure that ML and DL models trained on consistent scales. Target variables were engineered as follows: `target_class` indicating binary price direction (1: up, 0: down), and `target_reg` representing the actual next hour's opening price.

The balanced distribution of target classes was checked to avoid class imbalance issues that might bias the models. The dataset contained 8,595 negative and 8,919 positive samples, providing an almost balanced target distribution.

IV. Correlation Analysis

A correlation matrix was computed to explore inter-feature dependencies and potential multicollinearity. The heatmap in Fig. 4 visualizes these correlations, revealing significant positive relationships among cryptocurrency trading pairs and between certain market indices.

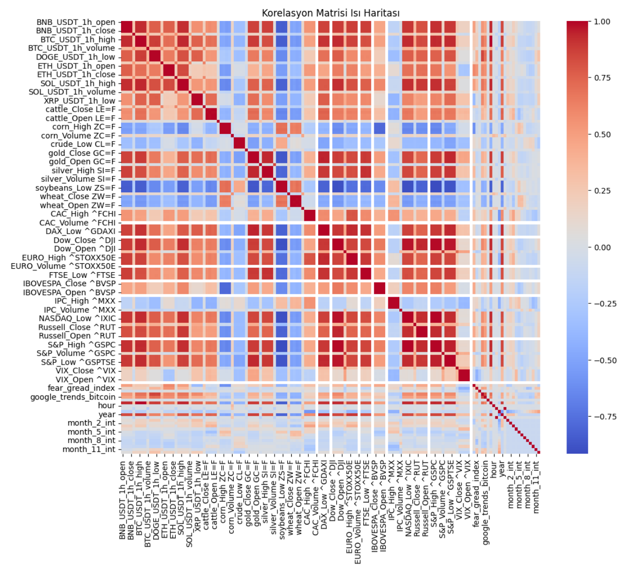

Fig. 4. Correlation Matrix Heatmap

Interestingly, Bitcoin and altcoin trading volumes showed stronger correlations with each other than with traditional stock indices, implying synchronized market dynamics across cryptocurrencies. Such correlations may indicate co-movement patterns that can be leveraged by predictive models; however, they may also introduce multicollinearity issues affecting feature selection algorithms.

V. Feature Selection

We employed ten feature selection methods to identify the most informative features: SelectKBest (chi2, f_classif, mutual_info), RandomForest, DecisionTree, ExtraTrees, Logistic Regression (L1), Recursive Feature Elimination (RFE), XGBoost, and LightGBM.

Each method ranked features differently, underscoring the diversity of selection biases inherent in various algorithms. Sample top features include:

- RandomForest: DOGE_USDT_1h_volume, XRP_USDT_1h_volume
- XGBoost: IBOVESPA_Open, NASDAQ_Open, month_7
- LightGBM: SOL_USDT_1h_volume, ETH_USDT_1h_volume

Volume-related features consistently appeared across multiple methods, suggesting their predictive significance in price movement modeling. The agreement across methods supports the hypothesis that trading volume plays a key role in short-term price fluctuations.

VI. Model Training and Evaluation

We trained five ML models (Decision Tree, Random Forest, KNN, SVM, Logistic Regression) and three DL models (DNN, CNN, LSTM). Evaluation metrics included accuracy, precision, recall, F1-score, training duration, and inference time.

TABLE II
Model Performance Summary

Model	Accuracy	Precision	Recall	F1
Decision Tree	49.96%	50.02%	49.96%	49.97%
Random Forest	50.73%	50.77%	50.73%	50.74%
KNN	47.30%	47.31%	47.30%	47.31%
SVM	49.81%	49.32%	49.81%	48.62%
Logistic Regression	49.41%	49.00%	49.41%	48.58%
CNN	51.56%	-	100%	67.48%
DNN	50.39%	-	-	-
LSTM	RMSE:61470	-	-	-

The CNN achieved the highest accuracy among models, although it exhibited a class imbalance issue by predicting the positive class for all instances.

VII. Confusion Matrix Analysis

Fig. 5 and Fig. 6 present the confusion matrices for Random Forest and CNN. While CNN achieved the highest accuracy, it failed to distinguish between classes, predicting only the positive class.

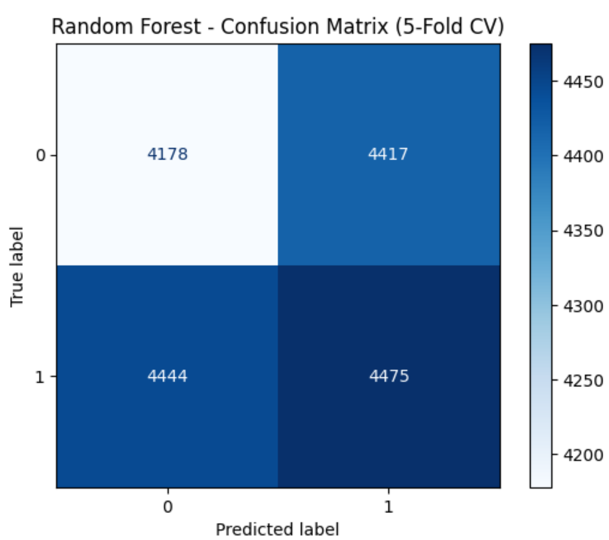

Fig. 5. Random Forest Confusion Matrix

This limitation artificially boosted recall while compromising class balance. On the other hand, Random Forest produced a more balanced matrix but accuracy remained close to random baseline, reflecting the inherent difficulty of predicting short-term price directions in highly stochastic markets.

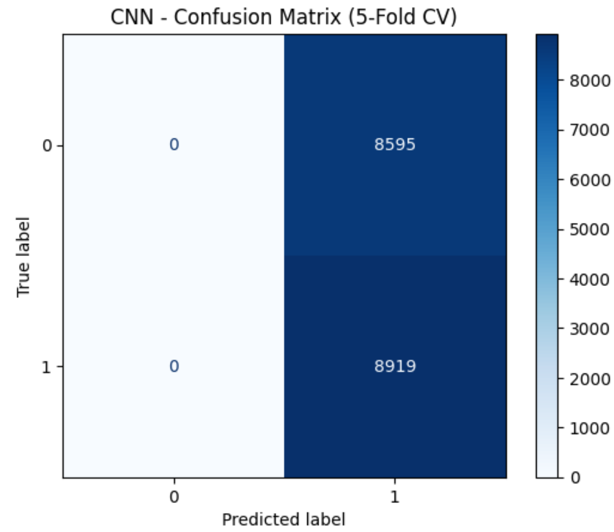

Fig. 6. CNN Confusion Matrix

VIII. Conclusion

This study conducted a comparative analysis of ML and DL models for predicting Bitcoin price direction. CNN achieved the highest accuracy but suffered from class imbalance. Random Forest provided more balanced predictions but accuracy remained close to random baseline. Feature importance analysis indicated trading volumes and closing prices as key predictors. Future work may explore sentiment analysis, blockchain metrics, and sequential models to enhance prediction robustness.

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