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Inequality Metrics as Early Warning Indicators of Bitcoin Market Instability

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Abstract: Existing Bitcoin price prediction systems mainly rely on traditional statistical models or basic financial indicators, which often fail to capture complex market patterns and the highly volatile nature of cryptocurrency markets. Many machine learning models use only historical price values and do not integrate statistical inequality measures such as the Lorenz Curve, Gini Index, or K-Value, which can provide insights into market distribution and stability. To overcome these limitations, the proposed system analysis historical Bitcoin price data from 2010 to 2021, including the open, high, low, and closing prices. The proposed framework incorporates the Lorenz Curve, Gini Index, and K-Value along with financial data, and a linear regression model is applied for time-series forecasting. The proposed model showed improvements of 1.46%, 6.87%, and 0.07% in RMSE, MAE, and MAPE, respectively, over the baseline. The results indicate that integrating inequality-based features improved prediction reliability and provided a better understanding of market behaviour.

Keywords: Bitcoin; Price prediction; Market instability; Lorenz Curve; Gini Index; K-Value

I. INTRODUCTION

Bitcoin is the first and most widely used cryptocurrency, operating on a decentralized digital network without the control of any central authority such as a bank or government. It was introduced in 2008 and became operational in 2009. Bitcoin uses blockchain technology, which records all transactions in a distributed ledger system, ensuring transparency and security. Figure 1 shows how Bitcoin is used.

Over the past decade, Bitcoin has gained significant popularity as a digital asset and investment option. Its market value has grown rapidly, reaching more than 1 trillion dollars in 2021. However, the price of Bitcoin is highly volatile and changes frequently due to factors such as market demand, investor sentiment, and global economic conditions.



Figure 1. How Bitcoin is used.

Because of this high volatility, predicting Bitcoin prices has become an important research area in financial data analysis. Machine learning techniques and time series forecasting methods are widely used to analysis historical price data and identify patterns that may help in predicting future price movements.

A. Problem Statement

The rapid growth of Bitcoin has attracted significant attention from investors, researchers, and financial institutions. However, predicting the price of Bitcoin remains a highly challenging task due to the volatile and unpredictable nature of cryptocurrency markets.

Another major challenge is that many prediction models do not effectively analysis the distribution and inequality patterns of price fluctuations. Statistical measures such as the Lorenz Curve, Gini Index, and K-Value can provide valuable insights into how price changes are distributed over time and how market instability affects prediction accuracy.

Therefore, there is a need to develop a hybrid prediction framework that combines machine learning techniques with statistical inequality analysis to better understand market behaviour and improve prediction accuracy. Such an approach can help capture both trend patterns and distribution characteristics, leading to a more robust and reliable Bitcoin price prediction system.

B. Related Work

Table 1 summarizes the related work reviewed, with the approach, key finding, and limitation or gap of each study.

Table 1. Summary of related work.

Authors (Year)	Approach	Key Finding	Limitation / Gap
Manna et al. (2022)	Analysis of social inequality indices in self-organized critical models	Inequality measures such as Lorenz curve and Gini index show universal behaviour in complex systems	Not specifically applied to cryptocurrency prediction
Zhang et al. (2023)	Deep learning based Bitcoin prediction using LSTM networks	LSTM effectively captures temporal patterns in cryptocurrency price data	Limited feature set; ignores market inequality indicators
Kim and Park (2023)	Hybrid machine learning model combining multiple algorithms	Hybrid models improve prediction accuracy compared to single models	Model complexity and high computational cost
Singh et al. (2023)	Ensemble learning techniques for Bitcoin price prediction	Ensemble models enhance robustness and prediction performance	Requires large training datasets
Chen and Zhao (2024)	Transformer-based time series forecasting for cryptocurrency markets	Transformers capture long-term dependencies in price trends	High computational requirements
Ahmed et al. (2024)	Deep reinforcement learning for Bitcoin trading prediction	Reinforcement learning can adapt to dynamic market conditions	Training instability and complex parameter tuning
Li et al. (2024)	Multivariate machine learning model using multiple market indicators	Incorporating multiple variables improves prediction accuracy	Not integrated with inequality measures
Kumar and Gupta (2024)	Statistical inequality analysis of cryptocurrency markets	Market inequality metrics help analysis price distribution behaviour	Not integrated with predictive ML models
Santos et al. (2025)	Hybrid deep learning framework for cryptocurrency forecasting	Combination of deep learning models improves prediction accuracy	High training time and model complexity
Wang and Zhou (2025)	Explainable AI for cryptocurrency price prediction	Improves transparency and interpretability of ML models	Slight training time and model complexity

Authors (Year)	Approach	Key Finding	Limitation / Gap
Patel et al. (2025)	Sentiment analysis with machine learning for Bitcoin forecasting	Social media sentiment improves price prediction	Dependent on noisy external data
Zhou et al. (2025)	Graph Neural Networks for cryptocurrency market prediction	Captures relationships between different cryptocurrencies	Complex graph construction required
Rahman and Islam (2026)	Inequality-driven machine learning framework for financial prediction	Inequality metrics enhance financial forecasting	Limited validation on cryptocurrency markets
Gupta et al. (2026)	Advanced regression models for Bitcoin time-series	Regression models provide stable baseline predictions	Limited validation on cryptocurrency markets

Manna et al. (2022) analysis social inequality indices in self-organized critical models and found that inequality measures such as the Lorenz curve and Gini index show universal behaviour in complex systems; this work was not specifically applied to cryptocurrency prediction. Zhang et al. (2023) used LSTM networks for deep learning based Bitcoin prediction and found that LSTM effectively captures temporal patterns in cryptocurrency price data, but with a limited feature set that ignores market inequality indicators. Kim and Park (2023) combined multiple algorithms in a hybrid machine learning model and found that hybrid models improve prediction accuracy compared to single models, at the cost of model complexity and high computational cost. Singh et al. (2023) applied ensemble learning techniques to Bitcoin price prediction and found that ensemble models enhance robustness and prediction performance, but require large training datasets.

Chen and Zhao (2024) used transformer-based time series forecasting and found that Transformers capture long-term dependencies in price trends, with high computational requirements. Ahmed et al. (2024) applied deep reinforcement learning to trading prediction and found that reinforcement learning can adapt to dynamic market conditions, but with training instability and complex parameter tuning. Li et al. (2024) built a multivariate machine learning model using multiple market indicators and found that incorporating multiple variables improves prediction accuracy; their model was not integrated with inequality measures. Kumar and Gupta (2024) carried out a statistical inequality analysis of cryptocurrency markets and found that market inequality metrics help analysis price distribution behaviour, but this was not integrated with predictive machine learning models.

Santos et al. (2025) proposed a hybrid deep learning framework for cryptocurrency forecasting and found that a combination of deep learning models improves prediction accuracy, with high training time and model complexity. Wang and Zhou (2025) studied explainable AI for cryptocurrency price prediction, which improves the transparency and interpretability of machine learning models, with slight training time and model complexity. Patel et al. (2025) combined sentiment analysis with machine learning for Bitcoin forecasting and found that social media sentiment improves price prediction, but the approach depends on noisy external data. Zhou et al. (2025) used graph neural networks for cryptocurrency market prediction to capture relationships between different cryptocurrencies, but complex graph construction is required. Rahman and Islam (2026) proposed an inequality-driven machine learning framework for financial prediction and found that inequality metrics enhance financial forecasting, with limited validation on cryptocurrency markets. Gupta et al. (2026) used advanced regression models for Bitcoin time-series prediction and found that regression models provide stable baseline predictions, also with limited validation on cryptocurrency markets.

C. Existing System

The existing Bitcoin price prediction system mainly uses historical market data and traditional financial indicators to forecast future Bitcoin prices. The key points of the existing system are as follows:

- It uses historical Bitcoin price data for prediction.
- It collects Open, High, Low, Close, and Volume (OHLCV) values.
- It uses basic machine learning algorithms such as Decision Tree, Random Forest, and K-Nearest Neighbour (KNN).
- It performs data preprocessing to remove missing values and duplicates.
- It divides the dataset into training and testing sets.
- It predicts future Bitcoin prices based on past market trends.
- It uses only financial indicators without additional statistical analysis.

The limitations of the existing system are as follows:

- Most models rely only on historical price data such as open, close, high, and low values.
- Traditional statistical models cannot capture complex and nonlinear market patterns.
- Cryptocurrency markets are highly volatile, making prediction difficult.
- Many systems ignore market sentiment and investor behaviour.
- Lack of integration of statistical inequality measures like Lorenz Curve, Gini Index, and K-Value.
- Existing models often require large datasets for training.
- Poor performance in real-time prediction environments.
- Lack of consideration of external factors such as regulations and global economic events.
- Difficulty in handling large and rapidly changing financial data.
- Prediction accuracy decreases during extreme market fluctuations.
- Existing approaches provide limited insights into price distribution and market inequality.

II. RESEARCH METHODOLOGY

A. Dataset

The dataset used in this project consists of historical price data of Bitcoin, from 2010 to 2021. It contains daily Bitcoin market records, with one row per date and the columns Date, Price, Open, High, Low, Vol., and Change %. The date uses the M/D/YYYY format. Price is the closing price for that day, Open is the daily opening price, High and Low are the day's maximum and minimum prices, Vol. is the trading volume (shown with K for thousands), and Change % is the daily percentage change in closing price. The data includes the financial attributes opening price, closing price, highest price, lowest price, trading volume, and date and time. The dataset was collected from reliable cryptocurrency data sources such as Coin Market, Yahoo Finance, and Kaggle, and contains daily Bitcoin price records over multiple years, which helps in analysing market trends and price fluctuations.

In addition to the original dataset, a new derived dataset was created after preprocessing. Additional statistical features were calculated to enhance prediction performance: Lorenz Curve values, Gini Index, and K-Value (an inequality measure). These new features help in analysing the distribution of price changes and market volatility, which improves the prediction capability of the hybrid model. The final dataset was divided into a training dataset (used to train the model) and a testing dataset (used to evaluate prediction accuracy).

B. Proposed Work

The proposed system utilized historical Bitcoin price data along with important financial indicators such as opening price, closing price, highest price, and lowest price. In addition to these conventional features, inequality measures including the Lorenz Curve, Gini Index, and K-Value were incorporated to analyse the distribution and stability of price fluctuations. A linear regression model was applied as the machine learning approach to perform time-series forecasting. The model was trained and tested using preprocess historical data, and its performance was evaluated using appropriate accuracy metrics.

Table 2 compares the existing and proposed work. The existing work uses traditional statistical models, uses only historical price data, and relies on basic financial indicators. The proposed work is a hybrid machine learning framework that integrates inequality metrics (Lorenz Curve, Gini Index, and K-Value) with linear regression and inequality analysis.

Table 2. Difference between existing and proposed work.

	Existing Work	Proposed Work
Approach	Traditional statistical models	Hybrid ML framework
Data / features	Uses only historical price data; basic financial indicators	Integrates inequality metrics (Lorenz Curve, Gini Index, K-Value)
Method	—	Linear Regression + inequality analysis

C. Architecture of the Proposed System

The architecture of the proposed system is shown in Figure 2. It consists of the following stages:

- 1) Data collection: historical Bitcoin data (2010–2021) from Coin Market Cap, Yahoo Finance, Kaggle, and Investing.com.
- 2) Data preprocessing: handling missing values, removing duplicates, data cleaning, normalization, and feature scaling.
- 3) Feature engineering: the Lorenz Curve, Gini Index, and Kolkata (K) Index, together with the mean, standard deviation, volatility, price change, and other derived features.
- 4) Dataset splitting: training data (80%) and testing data (20%).
- 5) Machine learning model training: Linear Regression, Random Forest Regression, Decision Tree Regression, and K-Nearest Neighbour (KNN).
- 6) Model evaluation: Mean Squared Error (MSE), Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), and the R^2 score (coefficient of determination).
- 7) Best model selection: selecting the model with the highest R^2 score and lowest error metrics.
- 8) Bitcoin price prediction: predicting future Bitcoin prices using the best performing model.
- 9) Market trend analysis and early warning detection: analysing market trends, detecting instability, and identifying early warning signals.
- 10) User / decision support: supporting investors, traders, and financial analysts, for better investment decisions.

The proposed system integrates statistical inequality measures (Lorenz Curve, Gini Index, and Kolkata Index) with machine learning algorithms to improve Bitcoin price prediction accuracy and detect market instability.

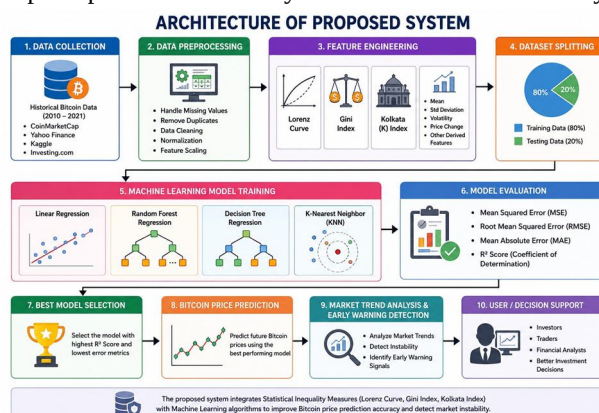


Figure 2. Architecture of the proposed system.

III. RESULTS AND DISCUSSION

The performance of the proposed model was compared with a baseline model using RMSE, MAE, and MAPE. Figure 3 shows the model performance comparison and the improvement of the proposed model over the baseline. The proposed model shows lower RMSE and MAE than the baseline. The improvement of the proposed model over the baseline is 1.46% for RMSE, 6.87% for MAE, and 0.07% for MAPE, as given in Table 3.

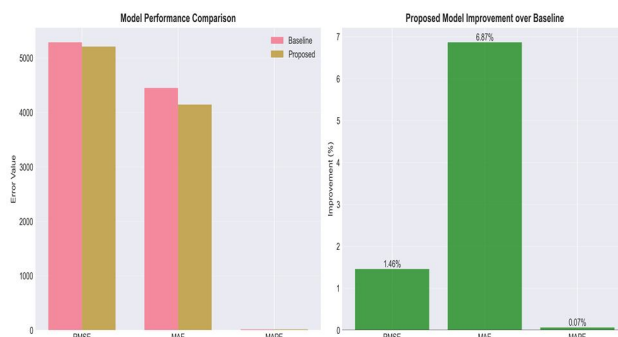


Figure 3. Model performance comparison (RMSE, MAE, MAPE) of the baseline and proposed models, and improvement of the proposed model over the baseline.

Table 3. Improvement of the proposed model over the baseline.

Metric	Improvement (%)
RMSE	1.46
MAE	6.87
MAPE	0.07

Figure 4 shows the actual and predicted prices over time steps for the baseline model and for the proposed model.

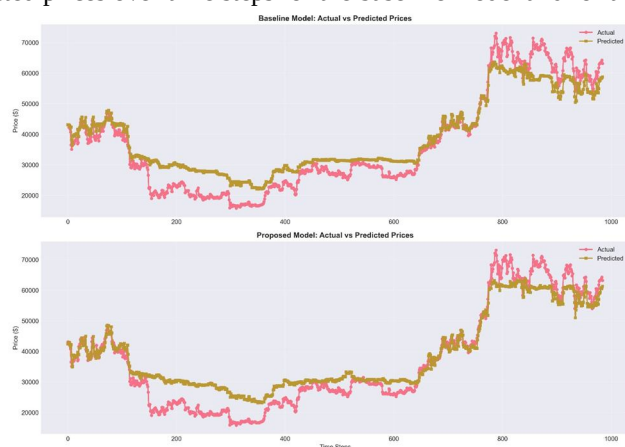


Figure 4. Actual versus predicted prices over time steps for the baseline model and the proposed model.

These results show that integrating inequality-based features improved prediction reliability and provided a better understanding of market behaviour. The study also highlights the importance of combining statistical analysis with machine learning techniques to capture both distribution characteristics and predictive trends.

IV. CONCLUSION

In this project, a hybrid framework for Bitcoin price prediction was developed by combining machine learning methods with statistical inequality analysis. The main goal of this approach was to improve the accuracy and reliability of cryptocurrency price forecasting while overcoming the limitations of traditional prediction techniques.

The proposed system used historical Bitcoin price data along with important financial indicators such as opening price, closing price, highest price, and lowest price. In addition to these standard features, statistical inequality measures like the Lorenz Curve, Gini Index, and K-Value were included to study the distribution and stability of price variations. These measures helped provide deeper insights into market volatility patterns that are usually not captured by conventional prediction models.

A Linear Regression algorithm was applied as the machine learning model to perform time-series forecasting. The model was trained and tested using preprocess historical data, and its performance was evaluated using suitable accuracy metrics. The experimental results showed that incorporating inequality-based features improved prediction reliability and helped in better understanding market behaviour. The study also emphasized the importance of integrating statistical analysis with machine learning techniques in order to capture both distribution characteristics and predictive trends. This hybrid approach is more effective in handling the dynamic and highly volatile nature of cryptocurrency markets compared to traditional models.

A. Future Work

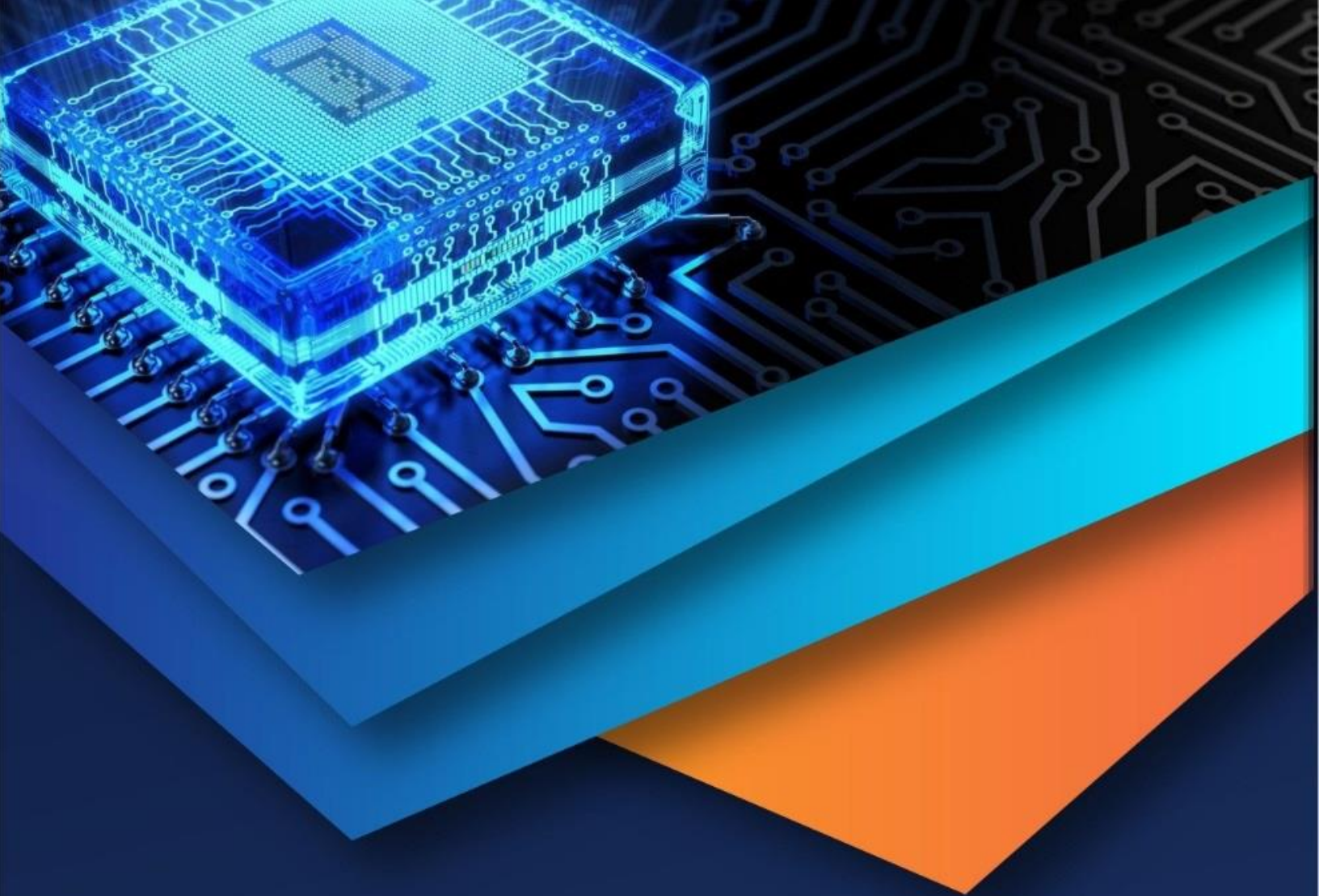
The following directions are identified for future work:

- Extend the system to support multiple cryptocurrencies such as Ethereum, Solana, Litecoin, Ripple, and Binance Coin.
- Implement advanced deep learning models including LSTM, GRU, Transformer Networks, and Temporal Convolutional Networks for improved long-term forecasting.
- Use blockchain on-chain analytics such as transaction volume, active addresses, mining difficulty, and hash rate as additional predictive features.

- Investigate high-frequency intraday Bitcoin data (hourly or minute-level data) to perform short-term trading prediction and volatility analysis.
- Develop a risk assessment and portfolio optimization module that uses the predicted prices and inequality metrics for investment decision support.
- Explore the application of reinforcement learning and autonomous trading agents for dynamic cryptocurrency trading strategies.

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