CRYPTOCURRENCY PRICE PREDICTION USING ENSEMBLE MODEL

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PROBLEM STATEMENT

- Cryptocurrency price prediction is a proposed system that utilizes machine learning and deep learning algorithms to predict the price of user-requested cryptocurrency.

INTRODUCTION

- Cryptocurrency has become a popular and highly volatile asset class in recent years. As a result, predicting the prices of cryptocurrencies has become a topic of great interest for traders, investors, and researchers alike.
- This project compares various model for cryptocurrency price prediction, which combines the strengths of models to improve accuracy.

DATA SET

- This project uses the yfinance library to download dynamic cryptocurrency data from yahoo finance.

EXISTING SYSTEM

- Paid System
- People with no programming knowledge cannot use the existing system
- Only available for crypto holders
- No open-source application available

PROPOSED SYSTEM

Anyone without prior knowledge of coding can use

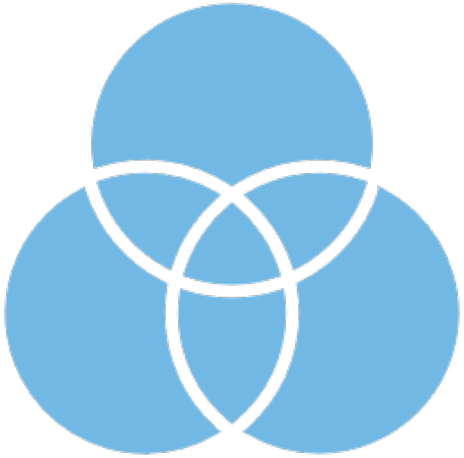
Uses deep learning model for prediction

Supports multiple currencies

Desktop application

LITERATURE REVIEW

- Prediction of the Variation in Price of Bitcoin Using Machine Learning
- Blockchain and Deep Learning-Based Models for Crypto Price Forecasting
- Cryptocurrency Price Prediction with LSTM and Transformer Models Leveraging Momentum and Volatility Technical Indicators
- A Novel Approach for Deep Learning-Powered Forecasting of Market Bottoms in Cryptocurrency and Stock Trading



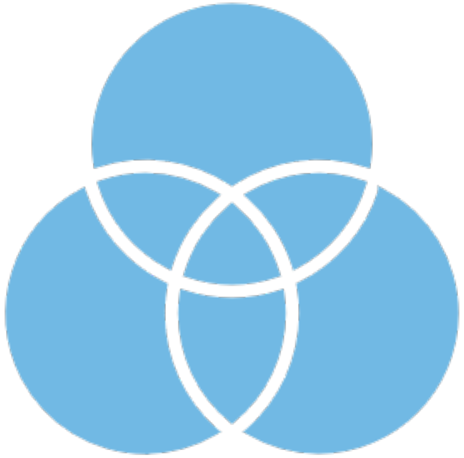
PREDICTION OF THE VARIATION IN PRICE OF BITCOIN USING MACHINE LEARNING

PUBLISHED YEAR – 2023

MONU SINGH

KAKUL NIGAM

Compares random forest, gradient boosting, and neural networks, and evaluated their performance using mean squared error and accuracy metrics.



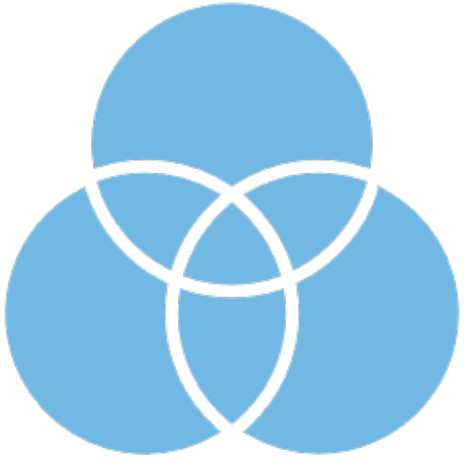
BLOCKCHAIN AND DEEP LEARNING-BASED MODELS FOR CRYPTO PRICE FORECASTING

PUBLISHED YEAR – 2023

P MEENA

S SAI MONIKA

- Uses the Python-based LGBM Neural network model to forecast market changes in real time and reduce investor losses.

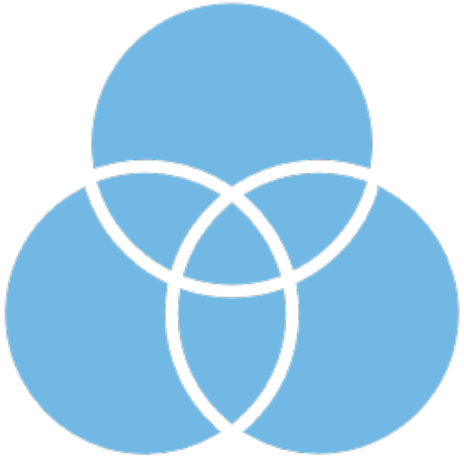


A NOVEL APPROACH FOR DEEP LEARNING-POWERED FORECASTING OF MARKET BOTTOMS IN CRYPTOCURRENCY AND STOCK TRADING

PUBLISHED YEAR – 2023

D.M.D.K. DASANAYAKE
H.Y. DILSHAN

- The study utilizes a Wasserstein Generative Adversarial Network (WGAN) with a Gated Recurrent Unit (GRU) to identify future market trends effectively. A classifier is added to the model as a substantial contribution to forecast future market bottoms by utilizing hidden WGAN features.



CRYPTOCURRENCY PRICE PREDICTION WITH LSTM AND TRANSFORMER MODELS LEVERAGING MOMENTUM AND VOLATILITY TECHNICAL INDICATORS

PUBLISHED YEAR – 2023

MARUTHI VEMULA
SIDDHARTH PENMETSA

- Considers Long-Short Term Memory (LSTM) and Transformer neural networks that use historical price features in addition to volatility and momentum technical indicators, along with historical price features,
- Momentum and volatility technical indicators such as Relative Strength Index (RSI), Bollinger Bands %B and Moving Average Convergence/Divergence (MACD) are not commonly used in cryptocurrency machine learning models.

METHODOLOGIES

- Machine learning models
- Time series models
- Deep learning models
- Hybrid models

MACHINE LEARNING MODELS

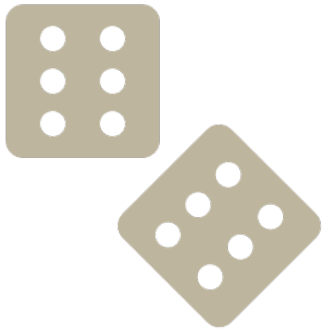
Linear Regression: Simple and interpretable model, suitable for basic price trend predictions.

Support Vector Machines (SVM): Effective for classification and regression tasks, providing flexibility in modeling complex relationships.

Random Forest: An ensemble method that combines multiple decision trees to enhance predictive performance.

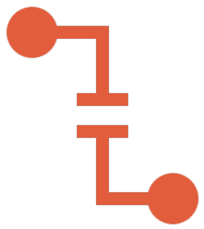
TIME SERIES MODELS

ARIMA (AutoRegressive Integrated Moving Average): Suitable for modeling univariate time series data, capturing trends and seasonality.

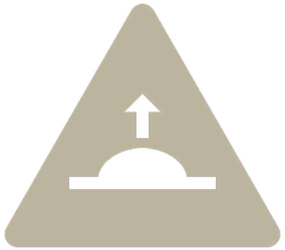


GARCH (Generalized Autoregressive Conditional Heteroskedasticity): Useful for modeling volatility in financial time series.

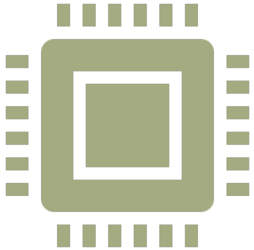
DEEP LEARNING MODELS



Recurrent Neural Networks (RNN): Effective in capturing sequential dependencies in time series data.



Long Short-Term Memory (LSTM) Networks: A type of RNN designed to address the vanishing gradient problem, commonly used for time series forecasting.



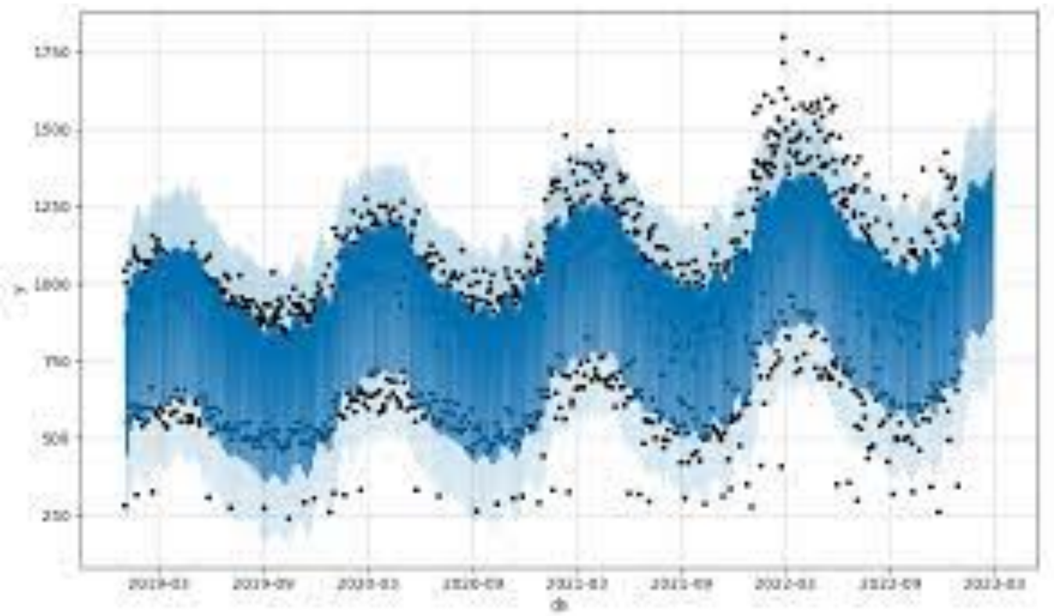
Convolutional Neural Networks (CNN): Useful for extracting spatial features, but less commonly used for time series data.

HYBRID MODELS

- **Prophet:** Developed by Facebook, suitable for forecasting time series data with strong seasonal patterns and holidays.
- **Ensemble Models:** Combining predictions from multiple models to improve overall accuracy.

PROPHET

- Prophet is an open-source algorithm that creates time-series models, and it was developed by Facebook's core data science team.
- It is robust to missing data and shifts in the trend and typically handles outliers well.
- To forecast business results, the algorithm seeks to give business users a strong and user-friendly tool that eliminates the need for a time series analysis expert.
- It is a forecasting procedure implemented in Python and R.



KEY FEATURES:

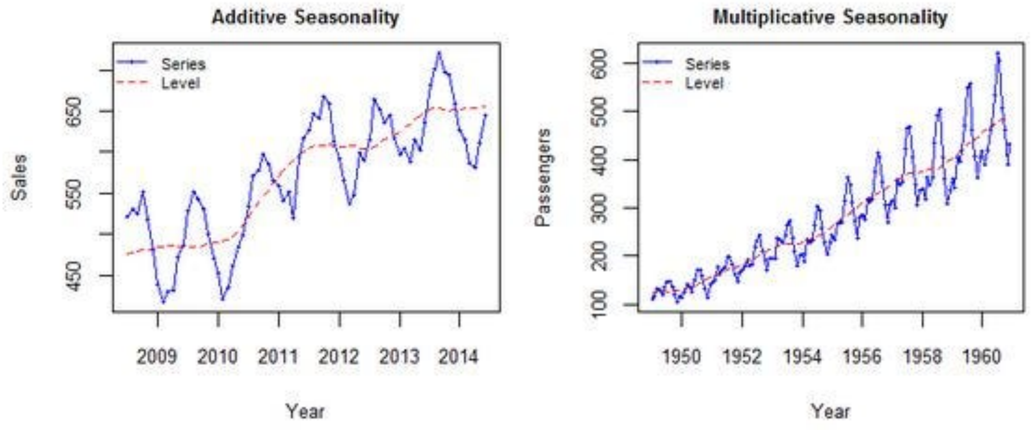
- **Robust Handling of Missing Data:** Prophet can handle real-world datasets with varying levels of data quality since it is resilient to missing data and outliers**.**
- **Automatic Seasonality Detection:** It does not require human pattern specification; it may automatically identify seasonal patterns in the data, such as weekly, monthly, or annual cycles**.**
- **Trend Forecasting:** It gives customers the capacity to anticipate changes in their time series by predicting both short- and long-term patterns in the data**.**
- **Uncertainty Estimation:** It provides insights into the degree of confidence in the predictions by generating uncertainty intervals around the anticipated numbers**.**

HOW IT WORKS:

1) Additive Decomposition:

Time series data is seen by the Prophet as a composite of three primary elements**:**

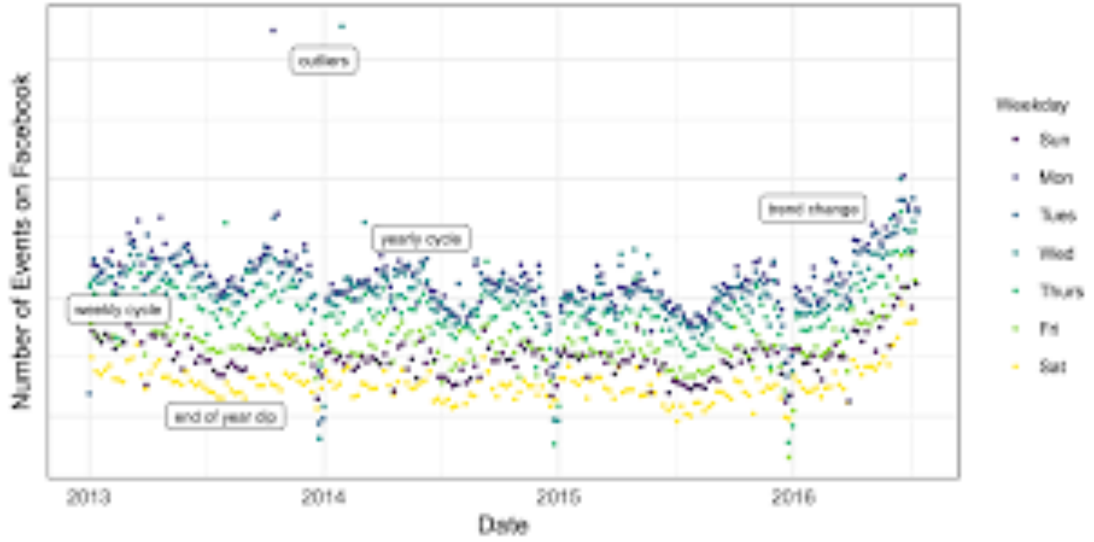
- **Trend:** This shows the general trend of the data over time**.**
- **Seasonality:** When repeated patterns or cycles appear in the data at regular intervals, they are referred to be seasonality. Seasonal variations in temperature or weekly fluctuations in retail sales are two examples**.**
- **Holidays/Effects:** This part takes into consideration any holidays or special occasions that can affect the time series data.



HOW IT WORKS:

2) Fourier Series:

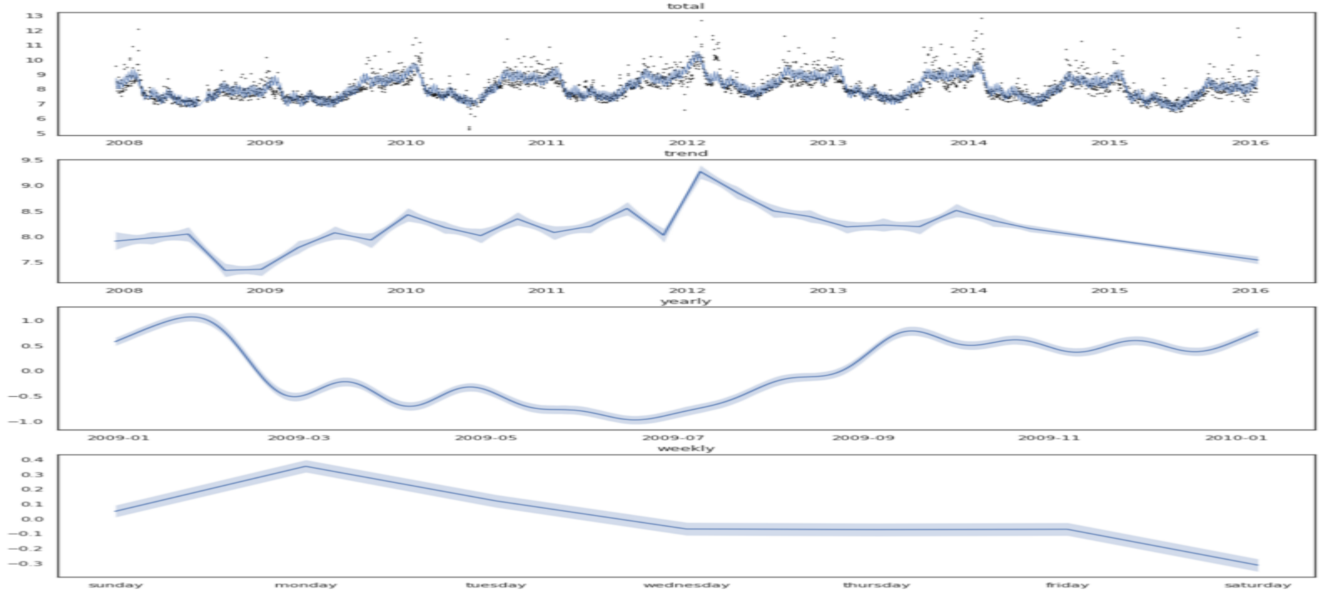
- Prophet models the periodic elements of the data, like daily, weekly, or annual seasonality, using the Fourier series.
- Complex periodic functions can be represented mathematically as the sum of smaller sine and cosine functions using the Fourier series.
- Prophet is capable of effectively capturing and modeling the cyclic patterns found in the data through the use of the Fourier series.



HOW IT WORKS:

3) Bayesian Framework:

- Prophet uses a Bayesian framework to estimate parameters and fit models.
- In Bayesian statistics, model parameter uncertainty is represented by probability distributions.
- Bayesian inference yields a posterior distribution that quantifies the uncertainty associated with each parameter, as opposed to a single point estimate for each parameter.

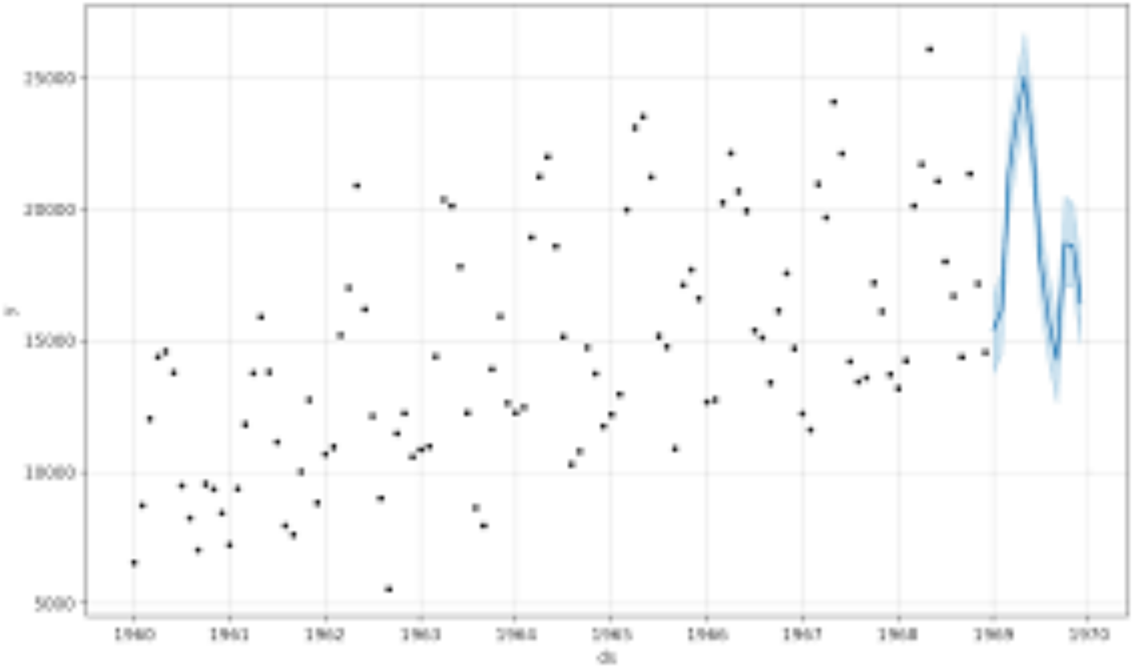


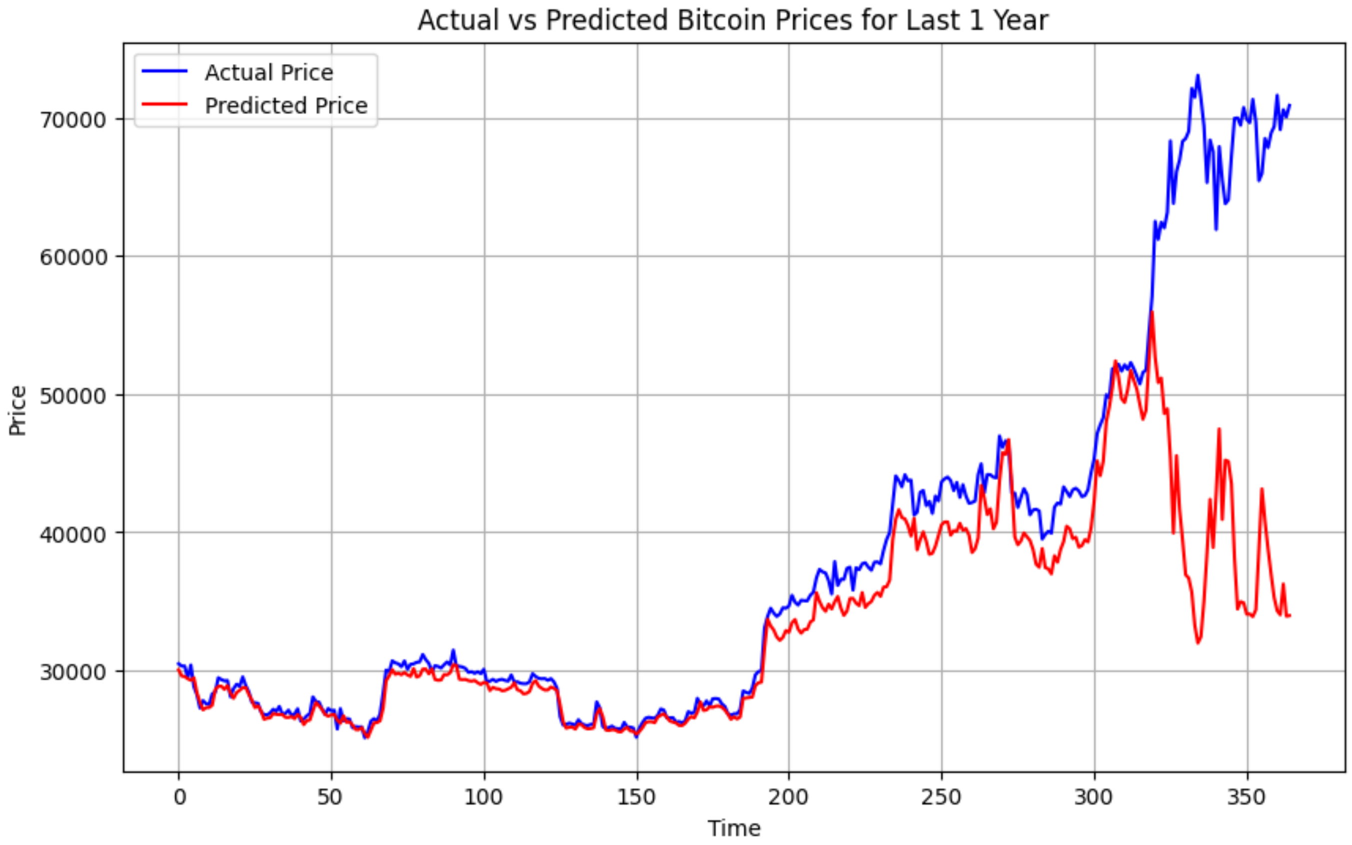
APPLICATIONS:

1) Supply Chain Management
2) Energy Forecasting
3) Healthcare
4) Weather Forecasting
5) Traffic and Transportation
6) Predictive Maintenance

CONCLUSION

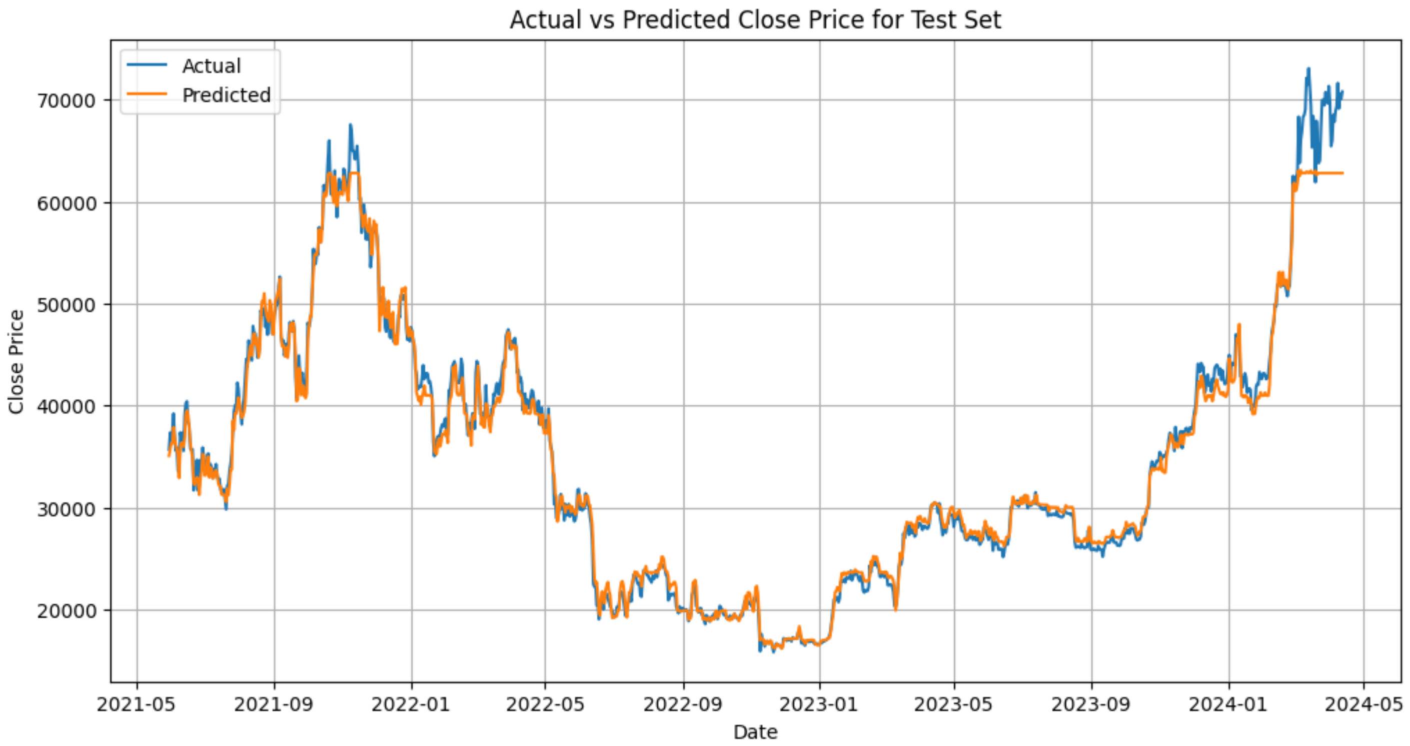
- Prophet is an effective forecasting tool that blends accuracy, versatility, and simplicity.
- It is an invaluable tool for analysts and forecasters in a variety of industries because of its strong handling of missing data, automatic seasonality recognition, and uncertainty estimation.

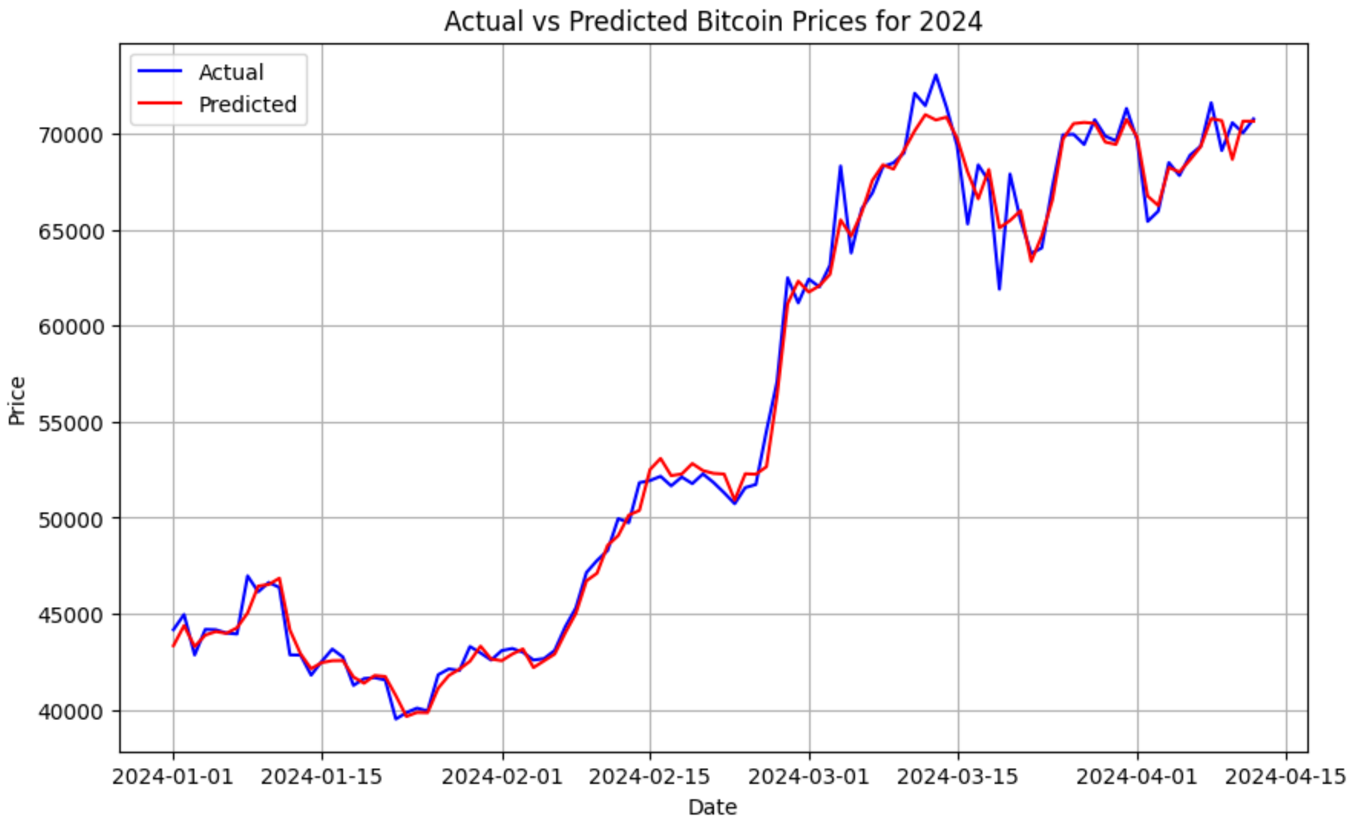



Actual vs Predicted Bitcoin Prices for Last 1 Year
Actual Price
Predicted Price
Price
70000
60000
50000
40000
30000
0
50
100
150
200
250
300
350
Time

SVR MODEL

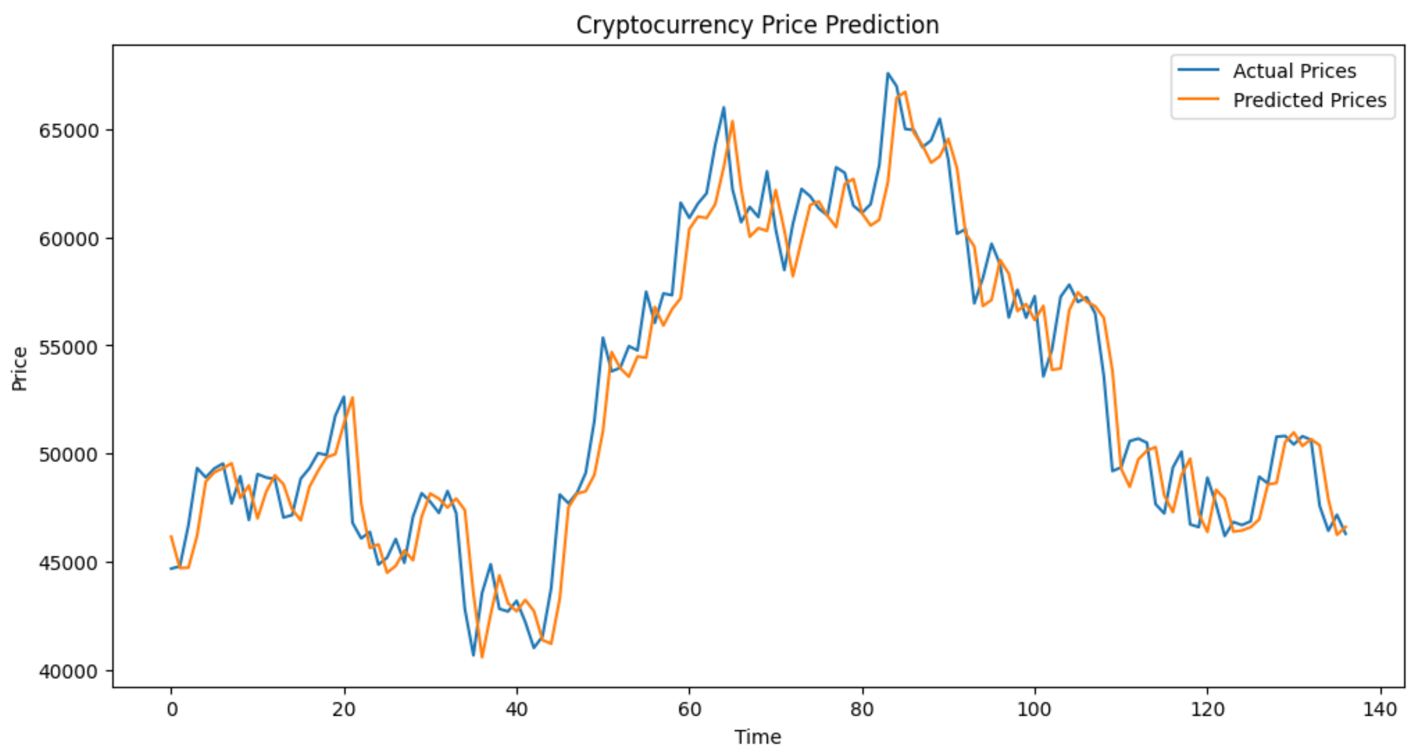
RANDOM FOREST MODEL



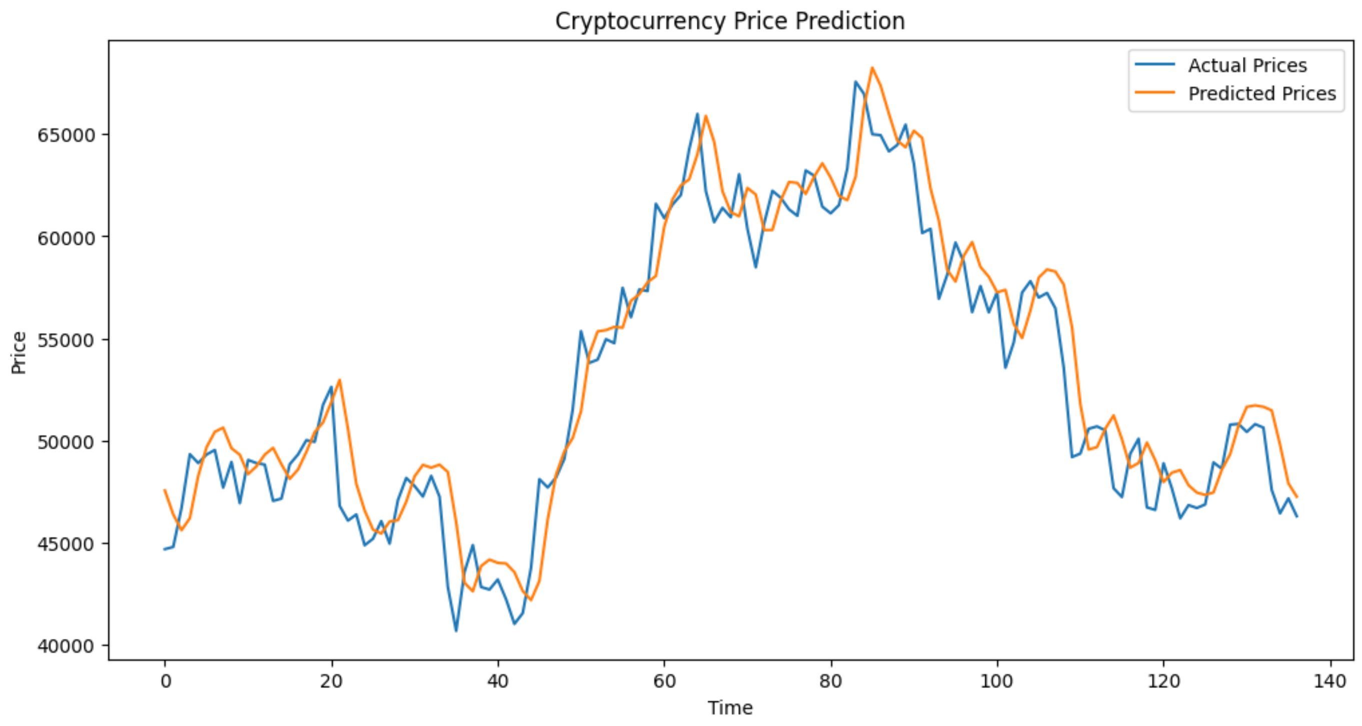


XGBOOST MODEL

RNN MODEL



Cryptocurrency Price Prediction
Actual Prices
Predicted Prices
Price
65000
60000
55000
50000
45000
40000
0
20
40
60
80
100
120
140
Time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Actual Prices
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60000
55000
50000
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40000
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20
40
60
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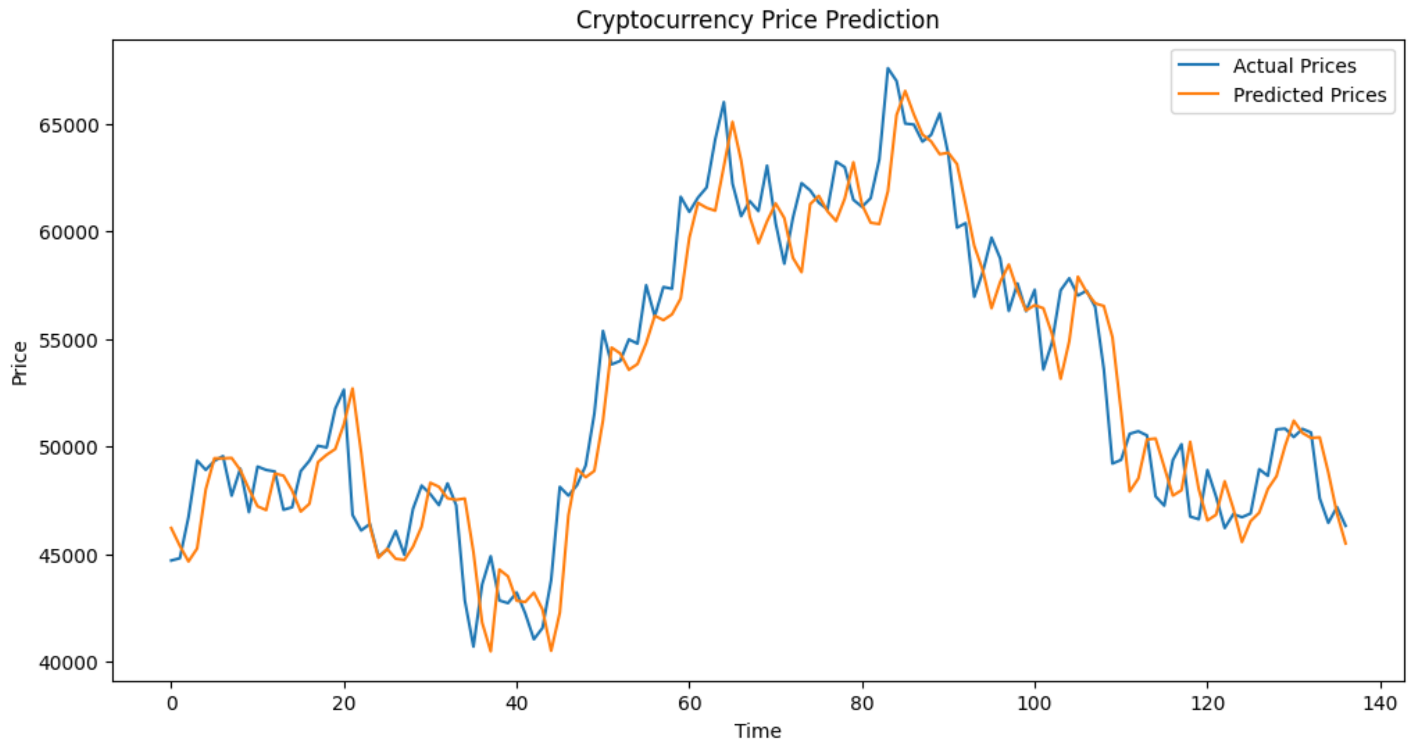
100
120
140
Time

LSTM MODEL

CNN MODEL



Cryptocurrency Price Prediction
Actual Prices
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65000
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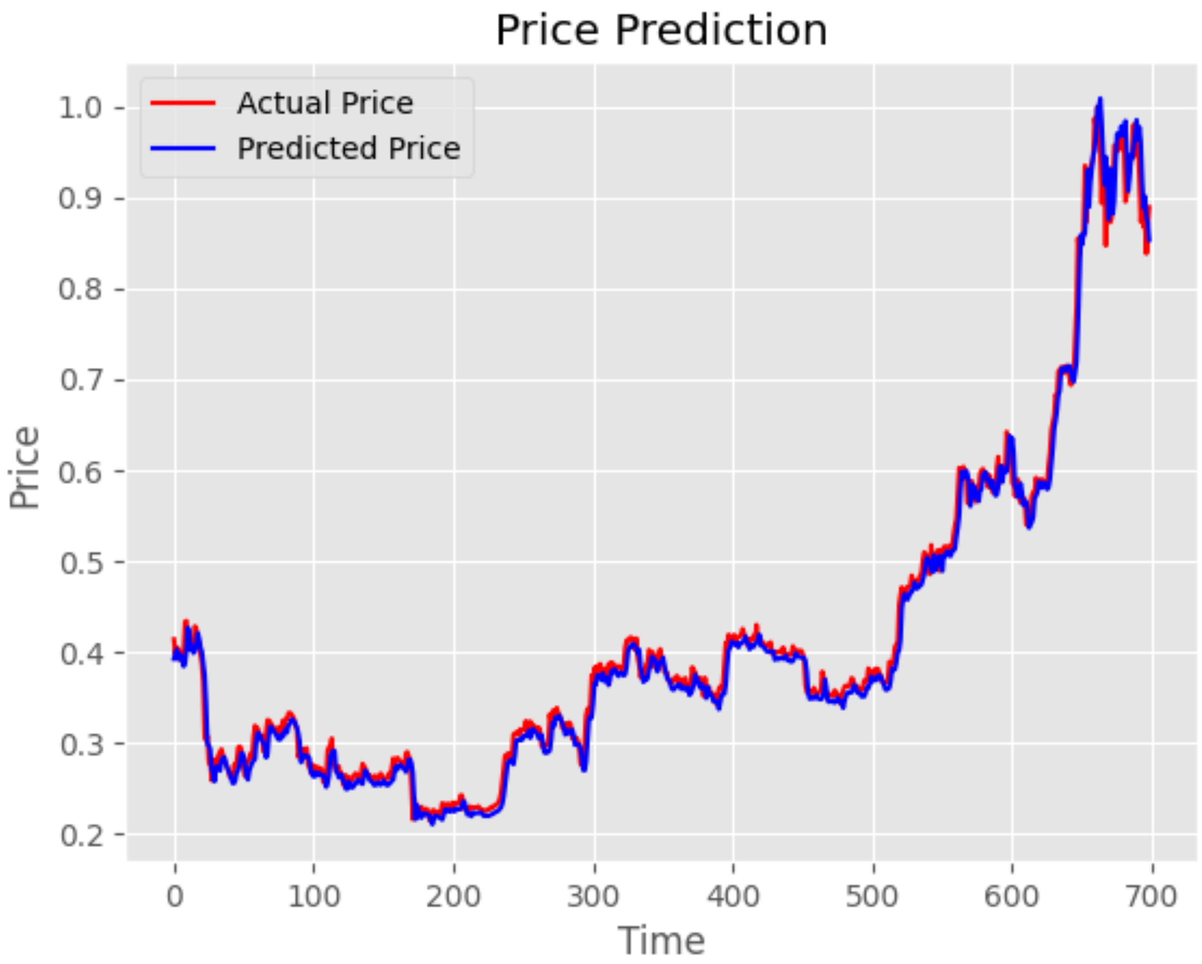

LSTM-GRU MODEL

COMPARING ACCURACIES

Model Name	Accuracy
SVR	76
Random Forest	83
XG Boost	97
RNN	96
LSTM	96.81
CNN	96
LSTM – GRU	97