Crypto Trend Prediction-based Web Application using Machine Learning

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**Abstract**. As digital finance moves forward quickly and crypto prices continue to swing unpredictably with growing need for accurate tools to predict price trends. Many investors struggle to make smart decisions because of unpredictable price swings and the lack of solid forecasting systems. This paper explores how machine learning especially models like Long short-term memory (LSTM), Recurrent Neural Network (RNN), Convolutional neural network (CNN), and Autoregressive integrated moving average (ARIMA) can be used to improve crypto price prediction. It also looks at how combining these models with external data such as market sentiment and technical indicators can boost accuracy. Existing platforms like CoinCodex, LiveCoinWatch, and CoinForecast.app are reviewed to highlight their pros and cons. Key forecasting challenges like unstable data, overfitting, and real-time updates are discussed. The study pulls together best practices for data handling and model building, offering insights that can help investors and researchers make better, more informed decisions in the crypto space.

# INTRODUCTION

Cryptocurrency has changed how the world handles money, offering a safer, more transparent, and decentralized option compared to traditional banking. Bitcoin leads the pack, with widespread use among individuals, businesses, and even big institutions. Still, the crypto market is famously unpredictable price swing fast due to changing public sentiment, new regulation, or tech update. This volatility makes it tough for everyday investors, especially those without tools to help them anticipate trends. In Malaysia, people are becoming more interested in crypto, and the government is working on making its use safer. But advanced tools that offer smart market insights are still hard to find locally. Around the world, machine learning is becoming a go-to method in finance for forecasting trends, yet it hasn’t been fully applied to crypto. This project fills that gap by building a user-friendly web platform that uses machine learning especially LSTM model to study past price data and predict short-term crypto trends. The goal is to give both global and Malaysian users a smarter, easier way to make informed investment decisions.

These days, predicting cryptocurrency prices have become more crucial than ever, mostly because of how quickly the market changes. As a result, it is no surprise that more investors are relying on data-driven methods and algorithms to help them make better decisions. In recent years, different machine learning (ML) and deep learning (DL) techniques have gained popularity. For instance, LSTM networks are often praised for their ability to catch long-term trends in time-series data, and many researchers have found that they can outperform older forecasting models [1], [2]. There is also a trend of combining LSTM with GRU to improve prediction accuracy while reducing the strain on computer resources, although these models can still be heavy to run [3],[4]. Besides that, RNNs (which are basically the backbone of LSTM) are quite common for analyzing trends across multiple cryptocurrencies at once [5], [6], [7], [8]. Some studies suggest that CNNs are especially good for picking up short-term signals, and when people use CNNs together with LSTM in a hybrid model, the results can be more accurate and easier to interpret [9], [10], [11]. Of course, classic models like ARIMA are still relevant, particularly for short-term forecasts or for smoothing out price volatility [12], [13], [14]. Interestingly, while there is all this research, most real-world platforms such as CoinCodex or CoinForecast still just offer live prices and basic charts, rather than advanced prediction tools. They barely apply deep learning or let users run their own forecasts. While CoinForecast.app does use some machine learning, it lacks customization features and deeper forecasting tools. Even though platforms like the previous mention offer basic real-time data and visual charts, they fall short when it comes to deep learning integration or letting users customize their forecasts. For example, CoinForecast.app has some ML features, but it does not let users change trend settings or view forecast graphs directly [15]. Overall, these platforms lack support for hybrid models or multivariate forecasting, and none of them use CNN to capture live data features. ARIMA, a simpler forecasting tool, is also missing from their systems even though it could benefit users who prefer straightforward trend predictions [16].

Last but not least, the CryptoTrend Forecasting System (CFA) was designed as a smarter alternative to address this issue. It brings together models like LSTM, CNN, and ARIMA in a user-friendly web platform. With CFA, users can pick their own historical time ranges, fine-tune forecast settings, and view results through downloadable visuals. The platform also supports statistical analysis for deeper insights. This setup follows the latest research recommendations and helps make advanced forecasting tools more accessible [17]. More than just a price tracker, CFA is a complete solution for investors, students, and researchers who want to better understand trends in the crypto space [18].

# TECHNOLOGY BACKGROUND

The CFA system develop using a python tool that make it easy to process a data, run a prediction, and create an interactive web app using streamlit. For the backend, it uses SQLite with DB Browser to manage user logins and its serverless setup. Historical cryptocurrency data price for example Bitcoin and Ethereum is kept in Microsoft Excel, which is handy for loading into the system. Tools like pandas, numpy and the requests library are used to clean the data and pull in live updates. The forecasting models are powered by scikit-learn and tensorflow, joblib and sklearn-intelex help with saving models and making them run more efficiently. For visualise, plotly is used to create interactive graphs. On the frontend, the platform uses streamlit, which lets you build clean, interactive web apps using just python no need to mess with HTML or javascript. Users can set their forecast preferences and instantly see the results. CSS are added using st.markdown() to improve the look and make the layout more user-friendly. This model helps deliver a smooth and user-friendly experience that both functional and easy to manage.

## System Overview

Figure 1 shows activity inside the CFA. Firstly, it starts at the login or registration screen. Users are taken to the regular user dashboard, or the admin dashboard depend on their role. From there, let say users, can choose a cryptocurrency, set the forecast time frame, and see predictions based on machine learning models like LSTM, ARIMA, RNN, or CNN. These forecasts use historical data pulled from the system database and appear in the forecast graph. Admins, on the other hand, can manage users, check a activity logs, and keeping an eye on all forecasts to make sure everything is running smoothly. The diagram helps break down how each action whether from a user or admin triggers different processes behind the scenes. In short, it shows how CFA keeps everything organized and role specific.

## System Functionalities

The CFA system has a functionality running in the background to make everything work smoothly which is:

1. Data Pre-processing: Before any predictions are made, the system will automatically clean up the historical crypto data, fixing missing values, formatting dates and times properly, and scaling numbers so the models can work with the data more precise and accurate.
2. Forecast Model Being Execute: Once the crypto data is ready, the platform uses machine learning models such as RNN, CNN and LSTM to forecast future crypto prices based on what the user has selected.
3. Visualization Forecast Results: After predictions are made, the results will show line graphs and tables.
4. Train and Update Model: The system can train and update the prediction models with new data over time.

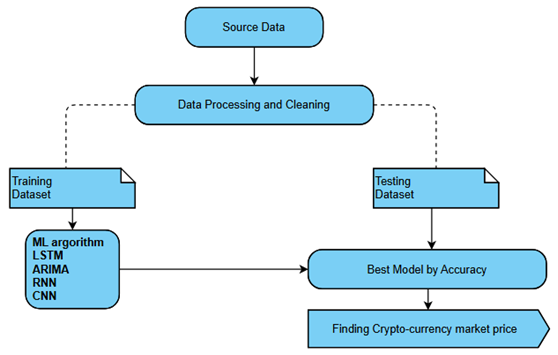
Figure 2 shows cryptocurrency price prediction source data being process and clean. It all starts with collecting data either from excel files and live API which includes important details like open and close prices, trading volume, and other indicators. Next, the system cleans the data by fixing the missing values by removing any unnecessary columns and organizing everything into a proper time series format. To make sure the model can learn very effective without overfitting, the data will split into training and testing sets.

Four main machine learning model that being used is:

1. LSTM: Identify long-term pattern in time-based data
2. ARIMA: Help with forecast short-term crypto prices by analyzing historical past data patterns.
3. RNN: Focuses on short-term patterns using feedback loops
4. A diagram of a system

   AI-generated content may be incorrect.CNN: Detect trends in organized time of segments.

**Figure 1.** Activity diagram

**Figure 2.** Cryptocurrency price prediction

Each of this model is train on historical data to learn the pattern and then test on unseen data to check how it performs. The system measures accuracy and precise using metrics such as Mean squared error, Root mean square error and Mean absolute percentage error. The model with the lowest error will be chosen to make the final predictions. Once it ready, the forecast results are displayed in graphs and tables for the user to view and make a prediction. Users can compare them with past trends and even download the past trend for their own use. The system also saves each forecast in a history section, so users can look back and track their previous predictions over time to time.

## Interface Design

The CFA interface is designed to be user-friendly and easy use, making sure users can navigate the platform smoothly no matter their tech background. Whether someone is new to crypto or more experienced, the layout is built to be straightforward and user-friendly. The system supports two main user roles regular users and admins. The design also follows modern web UI/UX practices and uses responsive layouts, so it looks and works great whether you're on a big monitor or a smaller laptop. The goal is to create a seamless and professional experience for everyone using the platform.

Figure 3 shows what the user homepage looks like after someone sets their preferences such as choosing a cryptocurrency, picking how far ahead they want to forecast, and selecting a start date for the historical data. The screen is split into two main parts: on the left is the panel for selecting parameters, and on the right are the results. The left sidebar, labelled "Select Parameters," let users pick things like the cryptocurrency they want to analyse (for example, Bitcoin - BTC/USD), the forecast horizon (such as 12 hours), and the starting point for historical data using a date picker. Everything is laid out with dropdown menus and a clearly marked "Forecast" button, so it’s simple to use. It also has an “Additional Configuration” section for more detailed adjustments to the historical data range. On the right side of the screen, users see the prediction results, which are broken down into three sections. At the top, "Current Statistics" panel that shows key figures for example the current price of the chosen cryptocurrency, the forecasted price, and the expected percentage change. These are displayed in separate boxes, making it easy for users to quickly get the main takeaways from the forecast.

A screenshot of a computer

Description automatically generated

**Figure 3.** A homepage for users after they select parameters, forecast horizon and date for historical data

# EVALUATION

To evaluate CFA performance, BTC/USD forecast using the LSTM model was simulated. The chart from Figure. 4 shown the historical (blue) vs. predicted (red) prices, with the forecast closely following actual trends. Performance metrics confirm high accuracy. These results demonstrate the model’s effectiveness in capturing short-term price movements with minimal error as shown in Figure 4.

A correlation heatmap of the dataset revealed that Open, High, Low, and Close prices are strongly correlated (correlation = 1), while Volume showed very weak correlation (< 0.1) with price features. This supports the system’s decision to use the Close price as the primary input for forecasting, ensuring model simplicity and avoiding redundancy as shown in Figure 5.

A screen shot of a graph

AI-generated content may be incorrect.

**FIGURE 4.** Historical vs Forecasted BTC price

A screenshot of a heatmap

AI-generated content may be incorrect.

**FIGURE 5.** Correlation matrix

1. Feature Engineering: Since price features are highly correlated, using just one (e.g., Close) as the input for prediction (as your CFA currently does) is justified and avoids redundancy. Including all highly correlated features wouldn’t significantly improve accuracy but could increase model complexity.
2. Volume Role: Volume is weakly correlated with price, meaning it’s not a strong predictor on its own. However, in advanced models (like CNN or attention-based networks), Volume could still add value as a supplementary feature to capture unusual activity spikes.
3. Model Simplification: The focus on using only the Close price as input for the LSTM, Random Forest, and Linear Regression models is justified by the correlation analysis. Since the Open, High, and Low prices exhibit near-perfect correlation with the Close price, including them would introduce redundancy without improving predictive performance. This approach promotes model efficiency and reduces the risk of overfitting.

# DISCUSSION

The evaluation shows that the LSTM model outperformed others with the lowest RMSE and MAPE, demonstrating its strength in capturing sequential patterns in volatile markets like cryptocurrency. This validates its use as the core forecasting model in CFA. The system's ability to combine multiple models with interactive forecasting and customizable parameters provides a significant advantage over existing platforms. However, its reliance on static Excel data and limited model tuning are current limitations. Future improvements should focus on integrating real-time data, optimizing models, and expanding forecasting horizons.

# CONCLUSION

The proposed CFA system combines machine learning with a user-friendly platform to predict short-term cryptocurrency trends. It achieves key goals in accuracy, customization, and visualization. While limited by static data and basic UI, it establishes a strong foundation for future enhancements like real-time data integration and long-term forecasting. Overall, CFA demonstrates the potential of machine learning in supporting informed decision-making in volatile crypto markets.

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