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Use of Artificial Intelligence in Ethereum Forecasting: The Deep Learning Models RNN and CNN with Ensemble Averaging Technique

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In the fast-evolving cryptocurrency market, accurately predicting Ethereum prices is crucial for investors, traders, and financial analysts. Traditional machine learning (ML) models often struggle to capture the market's complex dynamics due to their inability to consider all influencing factors. This study introduces an advanced ensemble machine learning approach to enhance Ethereum price prediction accuracy. By combining the strengths of Bi-directional Long Short-Term Memory (Bi-LSTM) and Convolutional Neural Network (CNN) models, our ensemble averaging method compensates for individual model weaknesses, improving forecast reliability and precision. Results show that our ensemble model offers significant advantages, particularly in terms of generalizability and resistance to overfitting with LSTM and CNN models and this technique is offering a more effective tool for navigating cryptocurrency market complexities. This research highlights the importance of ensemble learning in financial forecasting and provides a practical framework for developing superior predictive models. "Moreover, This study explores an advanced ensemble machine learning approach to enhance Ethereum price predictions, combining the strengths of Bi-directional Long Short-Term Memory (Bi-LSTM) and Convolutional Neural Network (CNN) models. While Bi-LSTM individually exhibits slightly higher performance in our tests, the ensemble method demonstrates enhanced stability and reliability, making it a valuable tool for navigating the unpredictable dynamics of the cryptocurrency market. We found that Bi-LSTM is good on its own, but the balanced approach of the ensemble model is far better, especially when it comes to generalizability and overfitting resistance. Insights into creating flexible and trustworthy prediction models are provided by this study, which highlights the possibilities of ensemble learning in financial forecasting.

Keywords: LSTM (Long short-term memory), CNN (Convolutional Neural Network), RNN (Recurrent Neural network, Ensemble learning, Deep learning

Introduction:

This paper investigates the causes of the effectiveness of the most well-known and accurate forecasting techniques. This study examines the impact of incorporating all relevant columns, such as 'Open', 'Close', 'High', 'Low', and Volume, on the accuracy of forecasting models. This research contributes to the field of cryptocurrency forecasting through the development of two distinct deep learning models, CNN and the variant of RNN the Bi-LSTM, and a state-of-the-art ensemble model to evaluate the accuracy of all models and the performance of individual and ensemble models. This research casts light on the most precise prediction methods by evaluating the accuracy level of individual models.

Researchers used diverse statistical, machine learning, and deep learning techniques to forecast various cryptocurrencies, but it is unclear which of these approaches is preferable. Because most of the studies are done over relatively short time periods and concentrate on forecasting the price of cryptocurrencies across a wide range of time intervals, the research is scattered and lacks generalization. In addition, the accuracy and evaluation of the performing models are grossly neglected.

Also, the models are very complicated, which makes it hard to use them in the real world because of the high costs of application, training, and forecasts. Lastly, due to the diverse datasets, pre-processing strategies, and experimental methodologies, the comparisons between the approaches are inconsistent, the experiments are difficult to reproduce, and their results are therefore unreliable. The primary objective of this paper is to overcome these limitations and shed light on the effectiveness of the most prominent approaches proposed to date in the literature for the crypto price prediction task. As a significant contribution, we develop a framework for comparing the accuracy of each deep learning model and its performance relative to ensemble learning models.

In this paper, we propose various deep-learning models and evaluate their efficacy in relation to Ethereum price forecasting. Additionally, we provide a novel ensemble learning approach that utilizes two deep learning architectures, namely Recurrent Neural Network (RNN) with Long Short-Term Memory (LSTM) and Convolutional Neural Network (CNN), for the purpose of predicting Ethereum values. The findings obtained from the LSTM and CNN models are used to implement an ensemble averaging strategy for result aggregation. Based on existing scholarly understanding, the main emphasis in the Ethereum forecasting study is on matters of safety and confidentiality. Previous research in the field of price forecasting has mostly used data such as price, volume, and textual content. These studies have primarily concentrated on datasets characterized by modest swings and short-term time periods. In our research, however, we use daily data from the past five years to predict the next day's price which means we worked on a long-term time period.

Literature Review:

The issue of forecasting future values based on historical data poses a significant challenge. This phenomenon is widespread in several practical contexts investigated by scholars, including but not limited to finance, climate prediction, and energy production. Financial time series forecasting is a very intricate issue that has garnered significant scholarly attention over the course of many decades. Nevertheless, the predictive capacity of conventional statistical models is constrained when it comes to forecasting financial time series data, mostly owing to the intrinsic volatility that characterizes such data. Predicting financial time series, especially stock prices, is a challenging task due to the presence of heavy-tailed distributions. Currently, the unsolved issue of stock market return prediction persists, with disputed conclusions [1]. The researchers highlighted the phenomenon of this type of prediction and their controversial results [2]. The recent rise in the value of cryptocurrencies, particularly Ethereum, has sparked a corresponding surge in the desire to forecast their future pricing [3]. Similar to the stock market, the precision of Ethereum price predictions will lead to enhanced financial gains for investors. In order to effectively capture complex nonlinear interactions among data variables, the analysis of time series pricing data requires the use of advanced techniques, such as deep learning models [4]. As a result, the anticipation of investment markets has emerged as a prominent subject of study within the domain of machine learning.

In addition, a wide array of scientific and financial approaches are used to forecast the future price fluctuations of cryptocurrencies [5]. ARIMA is a notable illustration of a financial and statistical methodology [6]. This model is often used by researchers for the purpose of predicting Ethereum values [7][8]. Additional models have been used in the field, including generalized autoregressive conditional heteroscedasticity (GARCH) models for predicting volatility in cryptocurrencies [9]. The GARCH model is considered a volatility forecasting model from many researchers' points of view [10] as well and diffusion processes in probabilistic forecasting of cryptocurrencies are also used for volatility forecasting [11]. Another cohort of researchers uses machine learning (ML) methods such as stochastic gradient boosting machines [12], linear regression, random forest, support vector machines, and k-nearest neighbors [13]. To enhance the precision of price forecasts, these methodologies use past data to ascertain the most important aspects that will shape future cryptocurrency values. A third body of literature uses deep learning (DL) models to predict the value of cryptocurrencies, building upon their recent achievements in quantitative finance [14]. The values of Bitcoin, Ethereum, and Litecoin have been forecasted via the use of several neural network models, including recurrent neural networks (RNN) such as gated recurrent unit (GRU) and long short-term memory (LSTM), temporal convolutional networks (TCN), and hybrid designs. Deep learning (DL) methods are considered to be useful for time series forecasting due to their ability to handle noise, their inherent capability to handle data sequences, and their capacity to learn nonlinear temporal relationships from these sequences [15].

Modeling And Approaches:

This section describes the procedures followed during the preprocessing and modeling phases of the investigation. The performance of CNN, Bi-LSTM, and Ensemble models is then assessed. The outcomes of each model's forecasting and prediction graphs are explained. In conclusion, our examination of the study's results is comprehensive and exhaustive. The objective of this study is to forecast the Ethereum price for the next day using CNN, Bi-LSTM, and ensemble learning techniques. The following research methods employ a state-of-the-art technique that will be a game changer in the field of Cryptocurrency price prediction.

- The historical data encompasses a diverse range of attributes, including the opening and closing prices. The usual methodology used in trade market forecasting entails the examination and analysis of these aforementioned features. The highest and lowest prices refer to the uppermost and lowermost values at which an Ethereum was exchanged during a certain time frame. The closing price is often defined as the last price at which a transaction using Ethereum takes place within a certain timeframe. The open price refers to the specific price at which a cryptocurrency commences trading at the commencement of a designated time period. We employed historical Ethereum daily pricing data spanning from 2017 to September 2023.
- To separate the dataset into training and testing sets, the prepare data function is created. It also prepares the data for input into all models.
- Development of Bi-LSTM, CNN, and ensemble Averaging models for deep learning

- Training consisting of Bi-LSTM, CNN, and Ensemble Averaging models.
- Models Forecasting
- Models' evaluation.
- Comparing the results obtained from Bi-LSTM, CNN, and ensemble models for Ethereum forecasting using various evaluation matrices, including RMSE, MAE, MAP, and Accuracy.

The URL to our proposed models on Git Hub is provided below. Ensemble-learning-model/Ensemble deep learning model.docx at main · Fozeeshan/Ensemble-learning-model (github.com)

Historical Data:

Ethereum historical price data is taken from Coin Market Cap from Nov 2017 till Sep 2023 https://coinmarketcap.com/

Table 1 explains our dataset. It contains Date, open, high, low, close, and volume columns. We are incorporating all columns to determine the influence of these column values on price forecasting. The close column is our targeted column, and the remaining columns are our input columns; therefore, the predicted next-day value is forecasted through the inclusion of all other columns of the data set. We applied the following methodology to data for predicting Cryptocurrency prices.

Table 1: Shows complete data columns of the dataset.

Parameter	Description	Data Type
Date	Date through that we can predict our Ethereum	Date
Open	Daily prices from which Ethereum values start	Number
High	The daily high price of the Ethereum	Number
Low	The daily low price of the Ethereum	Number
Close	These are basically our targeted values. It is the daily close price of the Ethereum	Number
Volume	The total volume of Ethereum at that close price.	Number

Proposed Structure of Our Ensemble Averaging Deep Learning Model:

In deep learning and machine learning in general, simple averaging is a foundational ensemble technique. In straightforward averaging, the predictions of multiple neural networks (or models) are averaged together. This technique is simple and effective for enhancing the accuracy of predictions. Regression and classification problems are both amenable to simple averaging. By merging the results of many distinct models, a simple averaging ensemble deep learning model is a method for improving forecast accuracy. The average of the predictions made by each model in the ensemble is calculated using this technique. The fundamental equation for simple averaging using two models (M1 and M2) is as follows:

(Prediction from M1 + Prediction from M2) / 2 = Final Averaged Prediction

This research applied an advanced ensemble Averaging deep learning model that included LSTM, a kind of recurrent neural network (RNN) often used for time series prediction, in conjunction with a convolutional neural network (CNN). The convolutional neural network (CNN) is a commonly employed network design within the field of deep learning. It is designed to learn directly from input and has shown high efficacy in tasks such as time series predictions and ensemble learning, where numerous individual models are combined to obtain improved generalization performance. Consequently, throughout the process of our study, we used an ensemble approach by combining our Bi-Long Short-Term Memory (Bi-LSTM) and Convolutional Neural Network (CNN) models in order to enhance the accuracy of our outcomes.

The Structure of Bi-LSTM:

Bidirectional -Long Short-Term Memory model is constructed and trained. Bidirectional LSTMs have both forward and backward passes and are effective at sequence prediction tasks. To prevent overfitting, the model architecture consists of three LSTM layers with variable numbers of units and dropout layers. A loss function and the Adam optimizer with a specified learning rate are used to compile the model. Early stopping is used to monitor the validation loss, allowing the model to end training when the validation loss no longer improves.

The Structure of CNN:

The convolutional Neural Network (CNN) model is constructed. The architecture of the model consists of a 1D convolutional layer, max-pooling, flattening, and densely connected layers. Similar to the LSTM model, the CNN model is compiled using a loss function and the Adam optimizer. Early stopping is also implemented.

Predictions with Bi-LSTM and CNN:

Using both Bi-LSTM and CNN models, predictions are made on the test data following training. The resultant predictions are presented as arrays. I used model_lstm and model CNN to make predictions on the X_test data in our program. The arrays y_pred_lstm and y_pred_cnn contain the predictions for the Bi-LSTM and CNN models, respectively.

Ensemble Averaging to Combine Predictions:

Sing ensemble averaging, the program combines the predictions of the Bi-LSTM and CNN models. This basic method creates a new prediction by averaging the predictions of the two models. In our program, y_pred_lstm and y_pred_cnn represent the predictions of the Bi-LSTM and CNN models, respectively. The ensemble prediction, y_pred_ensemble, is created by averaging y_pred_lstm and y_pred_cnn element-by-element. This ensemble forecast represents an aggregate estimate of the closing prices. Consequently, y_pred_ensemble comprises the predictions derived from the ensemble model created by aggregating the predictions of the individual Bi-LSTM and CNN models. The concept behind ensemble averaging is that it can increase the accuracy of predictions by minimizing the impact of individual model errors.

Evaluation Metrics:

In this model, two important evaluation metrics are used to assess the accuracy of predictions:

- The Mean Absolute Error (MAE) is a metric used to quantify the average absolute deviations between the observed Ethereum prices and the corresponding anticipated values. This provides a glimpse into the extent of the model's inaccuracies. In the given model's context, a reduced Mean Absolute Error (MAE) signifies a higher level of accuracy in the price predictions made by the model.
- Root Mean Squared Error (RMSE): This metric quantifies the square root of the mean of the squared errors in predictions. The method assigns more significance to substantial errors, hence exhibiting sensitivity towards outliers. Root Mean Square Error (RMSE) is a valuable statistic for comprehending the dispersion of forecast inaccuracies. Like Mean Absolute Error (MAE), a lower Root Mean Square Error (RMSE) suggests that the model's predictions are more precise.

These evaluation metrics are essential for determining the precision and dependability of the ensemble model's Ethereum price forecasts. In our research, each of the Bi-LSTM, CNN, and ensemble models' evaluation metrics are also generated. Included among the metrics are Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and an "Accuracy" score. We provided three visualization graphs for understanding the efficacy of the models. It depicts actual close prices versus predicted close prices for the Bi-LSTM, CNN, and ensemble models

Results and Discussions:

(Bi-LSTM) Model Performance:

Based on our analysis, the Bi-LSTM model, which takes advantage of the sequential nature of the data, proved to be the most effective. Crucial Performance Indicators: The model demonstrated exceptional performance, attaining a Mean Absolute Error (MAE) of 0.0061, a Root Mean Squared Error (RMSE) of 0.0091, and an accuracy of 98.47%. The performance of this model highlights the remarkable ability of the Bi-LSTM to identify and forecast the intricate dynamics associated with the price fluctuations of Ethereum.

CNN Model Performance:

In our research, the CNN model, which is renowned for its ability to recognize spatial patterns in data, also demonstrated impressive performance. Crucial Performance Indicators: With an MAE of around 0.010, an RMSE of around 0.012, and an accuracy of nearly 97.40%, the CNN model achieved these results. Although the CNN model offers significant insights into the price behavior of Ethereum, its overall accuracy is marginally inferior to that of the Bi-LSTM model.

Ensemble Model Performance:

By employing an aggregating technique, our ensemble model amalgamated the predictive prowess of the Bi-LSTM and CNN models, resulting in improved forecasting capabilities. Crucial Performance Indicators: The accuracy of 97.98%, MAE of 0.008, RMSE of 0.012, and MAE of 0.008 produced by the ensemble method demonstrate an interaction between the sequential and spatial data processing capabilities of the individual models. While demonstrating an enhancement compared to the CNN model, the ensemble model falls short in comparison to the Bi-LSTM model.

Visual Verification of Predicted Models:

Bi-LSTM Prediction:

The discrepancy between the Bi-LSTM model's predictions and the actual Ethereum prices (as illustrated in Figure 1) underscores this model's superior accuracy and capacity to closely monitor price trends.

CNN Predictions:

The efficacy of the CNN model is illustrated in Fig. 2, which compares its predictions to actual prices. However, it is worth noting that the CNN model exhibits a slightly lower precision in comparison to the Bi-LSTM model.

Ensemble Model Predictions:

The predictions generated by the ensemble model are presented in Figure 3. This visual representation provides strong evidence of the model's ability to accurately forecast Ethereum price fluctuations, although it does not outperform the performance of the Bi-LSTM model.

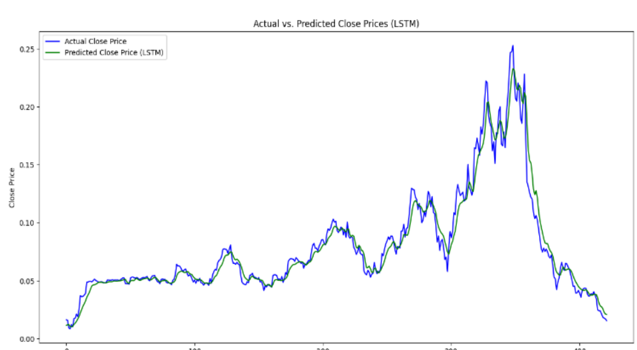

Figure 1: Ethereum prediction with Bi-LSTM actual vs predicted

Table 2: Results of the Study:

Matric	Bi-LSTM	CNN	Ensemble
MAE	0.0061	0.010	0.008
RMSE	0.0091	0.015	0.012
ACCURACY	98.47%	97.40%	97.98%

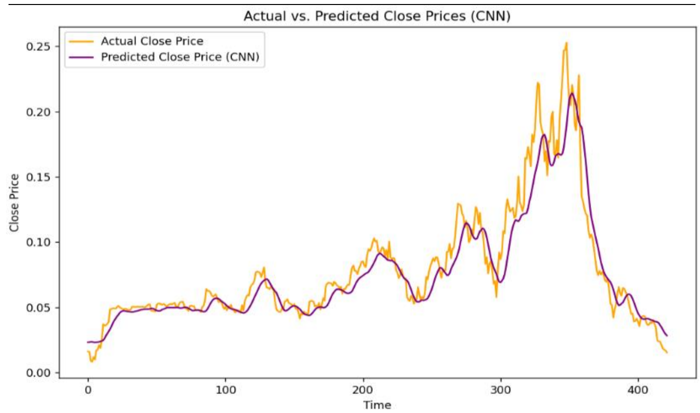

Figure 2: Ethereum prediction with CNN actual vs predicted.

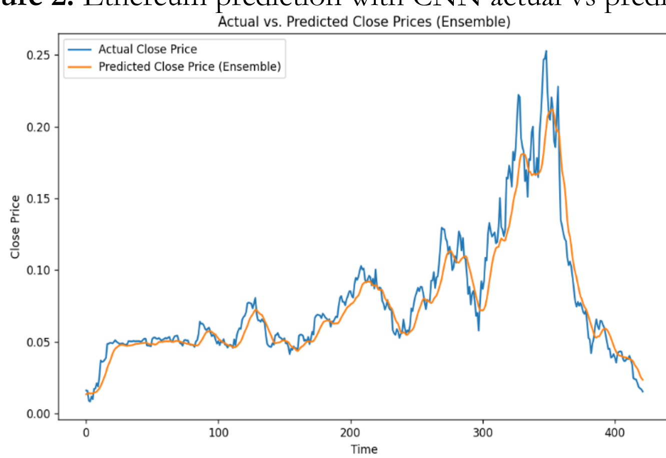

Figure 3: Ethereum prediction with Ensemble learning model actual vs predicted.

Conclusion:

Ethereum price forecasting is a complicated and intriguing undertaking for investors, traders, and financial experts in the ever-changing cryptocurrency market. This research endeavor aimed at simplifying the process of predicting Ethereum prices. We strived to find the best method for forecasting Ethereum prices by thoroughly analyzing several deep learning models, such as Bi bi-directional Long Short-Term Memory (Bi-LSTM), Convolutional Neural Network (CNN), and a novel ensemble technique. Our results show how the Bi-LSTM model outperformed the competition; it used sequential data analysis to predict Ethereum prices with unprecedented precision. With an astounding accuracy of about 98.47%, the model proved itself to be a formidable instrument for predicting cryptocurrency prices on its own

The ensemble model, which integrates Bi-LSTM and CNN models, as well as the CNN model on its own, provided useful information about future price changes; nevertheless, they were unable to outperform the Bi-LSTM model in terms of prediction accuracy but it is showing that at a stage where CNN has stopped improving the results, by ensembling we achieved the better results than individual CNN. The significance of choosing a model that is tailored to the data and the forecasting objective is highlighted by this discovery. Finally, our analysis proves that the Bi-LSTM model can accurately anticipate Ethereum prices, which is a huge step forward for cryptocurrency forecasting. It further highlights the possible advantages and disadvantages of using ensemble techniques in this setting. In light of the ever-changing cryptocurrency market, this study lays the groundwork for further research into improving prediction models by some more ensembling techniques and provides useful information for traders trying to make sense of Ethereum's intricate trading platform.

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