ARTIFICIAL INTELLIGENCE-BASED MODEL - A KEY TECHNIQUE IN DIGITAL ECONOMY DEVELOPMENT FOR CRYPTOCURRENCY PRICE PREDICTION

Mariya Paskaleva

South-West University "Neofit Rilski", Blagoevgrad
Bulgaria

Corresponding Author, e-mail: m.gergova@abv.bg

Abstract: This research examines the application of Long Short-Term Memory (LSTM) neural networks for predicting cryptocurrency prices, with a focus on Bitcoin (BTC) and Ethereum (ETH), the two dominant digital assets with the highest market capitalization. The study addresses the critical challenge of accurately forecasting cryptocurrency price movements in highly volatile markets, which is essential for informed investment decision-making in the digital economy. The methodology employs LSTM models trained on historical closing price data from 2014 to 2024 for Bitcoin and from 2017 to 2024 for Ethereum, utilizing an 80:20 training-to-testing ratio. Results demonstrate exceptional predictive accuracy with R^2 values of 99.08% for Bitcoin and 97.44% for Ethereum, while MAPE values remained low at 1.8% and 1.9%, respectively. The study concludes that LSTM models effectively capture complex patterns in cryptocurrency price movements, providing reliable short-term forecasting capabilities and contributing valuable insights to the intersection of artificial intelligence and digital economy development.

Key words: LSTM, Bitcoin, Ethereum, cryptocurrency prediction, neural networks, time series forecasting.

1. INTRODUCTION

Science and technology continually improve, prompting investors to predict the prices of financial instruments, including stocks, bonds, and cryptocurrencies. Forecasting stock market trends is a critical research area. Due to inherent risks and unpredictable price fluctuations, cryptocurrencies raise investor caution about market trends [1]. Cryptocurrency prices are of interest to researchers worldwide. Cryptocurrency price dynamics are unstable and depend on various factors, including transaction prices, mining difficulty, market trends, popularity, alternative coin prices, stock market fluctuations, public sentiment, and legal aspects [2]. The above factors determine crypto market volatility, making it difficult to predict its dynamics.

This paper proposes a methodology for cryptocurrency price prediction using LSTM neural networks, focusing on Bitcoin (BTC) and Ethereum (ETH), the leading cryptocurrencies by market cap. It addresses the critical gap in reliable forecasting tools for the digital economy by developing optimized LSTM architectures tailored for cryptocurrency price dynamics, showcasing LSTM models as essential tools for informed decision-making in volatile markets. This research targets the challenge of accurately forecasting price movements in these markets, crucial for investment decisions. Unlike traditional financial instruments, cryptocurrency prices are influenced by unique factors such as technological developments, regulatory changes, market sentiment, and network adoption rates, necessitating specialized predictive approaches to capture these complexities.

The methodology uses LSTM models trained on historical closing prices, employing data normalization techniques and optimal training parameters for better forecasting accuracy. The study validates this approach through performance evaluation and visual analysis of predicted versus actual price movements, demonstrating the models' ability to capture market dynamics and provide reliable short-term predictions.

2. LITERATURE REVIEW

Traditional statistical time series models are effective for price forecasting. However, machine learning and deep learning significantly enhance the capture of long-term information, yielding better results. While machine learning is well-established in stock price forecasting, its effectiveness in cryptocurrency forecasting is limited. This is due to cryptocurrency prices being influenced by various factors, including technological advancements, competition, supply and demand pressures, economic issues, security concerns, political factors, and innovative strategies.

Some models analyze the short-term dynamics of top cryptocurrencies—Bitcoin, Ethereum, and Ripple—using complex forecasting models, such as artificial neural networks (ANNs), random forests (RFs), and binary autoregressive trees (BARTs). Results show that ANN and BART achieved an average accuracy of 63% in predicting the directional movements of the studied variables [3].

Advanced machine learning forecasting models predict the future values of cryptocurrency components. More specifically, their primary goal is to predict the closing prices of the CCI30 index and the nine leading cryptocurrencies, thereby assisting investors in informed investment decisions. Their research utilizes machine learning models, including gradient boosting trees, artificial neural networks, k-nearest neighbors, and stable ensemble learning models. Ensemble models and gradient boosting trees show the best forecasting results, which were compared with similar contemporary models considered in the literature [4].

Accurate results are obtained in [5] when applying the Gated Recurrent Unit (GRU) forecasting model. However, their highly complex prototype complicates the expected results in this constantly changing environment. Furthermore, the selected features are insufficient to predict Bitcoin prices, as various factors such as social media, policies, and laws that each country announces for working with digital currency can significantly affect Bitcoin price fluctuations. When applying a comparative analysis of four different price forecasting models — recurrent neural networks (RNN), logistic regression, support vector machines, and autoregressive integrated moving average (ARIMA) — it is found that ARIMA's forecasting performance extends beyond the next day [6]. In the same research, it is proven that the RNN model can accurately predict price fluctuations for up to six days. The logistic regression model can give accurate results only if a separable hyperplane exists.

The authors of a study employ a hybrid approach that combines multi-scale residual blocks with an LSTM network to predict Bitcoin prices [7]. However, their work lacks comprehensive indicators to measure investor attention, which could enable more timely detection of Bitcoin market instability and result in more accurate forecasts. Others [8] investigate deep learning models such as GRU and LSTM, yet their research fails to explore further enhancements for improving model accuracy by considering various parameters. The feasibility of predicting Bitcoin prices is evaluated using an LSTM (Long Short-Term Memory) model [9]. The author examines the model's theoretical foundations and its application in forecasting. Results indicate that LSTM is valuable for predicting Bitcoin price fluctuations, but its high data requirements and basic theory limit its effectiveness. Real-life, unpredictable factors, such as psychological behaviors, cannot be easily represented in models. However, the LSTM model's flexibility suggests that future models based on it may yield improved forecasting performance. These findings guide financial data price forecasting using the LSTM model. In other research [10], Bitcoin prices are identified using high-frequency data, where XGB and SDA algorithms achieve accuracies of 66% and 65.3%, surpassing benchmarks. They use two datasets: one with aggregated daily Bitcoin prices and another with real-time trading data at 5-minute intervals. Similarly, the trends of Bitcoin and Ethereum are examined using internal indicators to uncover the network's price influences [11]. The authors apply machine learning (ML) techniques, such as LSTM and regression, to validate model accuracy. Bitcoin data from the "Blockchain" API covers April 2016 to May 2018, and Ethereum data is from "Etherscan" for the same period. Their findings reveal that LSTM achieves higher accuracy with minimal error in Bitcoin.

3. METHODOLOGY

The LSTM model, developed by Hochreiter and Schmidhuber, is an advanced version of the recurrent neural network (RNN). LSTM (Long Short-Term Memory) addresses the vanishing gradient problem in traditional RNNs, where small gradients hinder learning long-term dependencies. LSTM networks feature a memory cell that retains information over time, controlled by three gates: the input gate, the forget gate, and the output gate. The input gate regulates how much new data is stored, the forget gate decides what information to discard, and the output gate determines what is output. This architecture enables selective memory management, making LSTM particularly effective for sequential data tasks such as natural language processing, speech recognition, and time series analysis.

Backpropagation through time minimizes the loss function as the LSTM model identifies optimal parameters, including weight matrices and bias vectors for each gate and the output layer. Gradient clipping regulates the size of gradients during training, thereby addressing potential issues with vanishing or exploding gradients. LSTMs excel at recognizing patterns in historical price data to forecast future prices, using past prices to predict each subsequent price. The loss function measures the difference between predicted and actual prices, refining model training. The LSTM architecture comprises three components, each serving a distinct role.

Various indicators and metrics, including MAE, MSE, MAPE, and R^2, were used to evaluate the models. The smaller the value of the first three indicators, the better the model's performance. A larger R^2 value corresponds to a more effective model.

Table 1. LSTM Model Metrics

Metric	***Abbreviation***	***Equation***	***Description***
Root Mean Square Error	*RMSE*	$\sqrt{\frac{\sum_{t=1}^{n}(Q'_t - Q_t)^2}{n}}$	*RMSE is the standard deviation of errors. Lower RMSE value indicates better fit.*
Mean Absolute Error	*MAE*	$\frac{\sum_{t=1}^{n} \lvert Q_t - Q'_t \rvert}{n}$	*MAE is the absolute difference between the measured and simulated values. Lower MAE values indicate lower error.*
Coefficient of Determination	*R^2*	$[\frac{\sum_{t=1}^{n}(Q'_t - \overline{Q'})(Q_t - \overline{Q})}{\sqrt{\sum_{t=1}^{n}(Q'_t - \overline{Q'})^2}\sqrt{\sum_{t=1}^{n}(Q_t - \overline{Q})^2}}]^2$	*R^2 provides the intensity of the relationship between measured and simulated values. Its value ranges from 0 to 1, closer to 0 shows lower correlation, while close to 1 represents high correlation.*
Mean Square Error	*MSE*	$\frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y})^2$	*MSE represents the difference between original and predicted values, extracted by squaring the mean difference in the dataset.*
Mean Absolute Percentage Error	*MAPE*	$MAPE = \frac{1}{m}\sum_{t=1}^{m}\left\lvert\frac{y(t) - \hat{y}(t)}{y(t)}\right\rvert$	*This is an indicator used to evaluate the accuracy of a forecasting model.*

			MAPE measures the average percentage difference between predicted and actual values. MAPE is often expressed as a percentage. This is particularly useful when it is necessary to understand the accuracy of a model relative to the scale of the data being measured.

The stages used for forecasting with the LSTM method in this research are described in Table 2.

Table 2. Stages in LSTM Model Implementation

Stage	***Test Name***	***Input***	***Expected Output***	***Obtained Output***	***Status***
1	*Data array loading*	*CSV file*	*Data array reading*	*Data array loading*	*Successful*
2	*Data array division*	*Training set - 80%; Test set - 20%*	*Divide training from test set*	*Divided data array*	*Successful*
3	*Model training*	*Training data set, random value, predicted class*	*Training with best accuracy*	*Training with best accuracy*	*Successful*
4	*Model validation*	*Number of epochs*	*Model validation with best fit*	*Model generation*	*Successful*
5	*Accuracy and error percentage prediction*	*Precision*	*Graphical representation of expected and predicted accuracy*	*Graphical representation of predicted accuracy in cryptocurrency price dynamics*	*Successful*
6	*Test set*	*Test column*	*Predicted accuracy*	*Predicted accuracy*	*Successful*

The choice of the two cryptocurrencies, Bitcoin and Ethereum, is based on the market capitalization indicator. The total share of BTC and ETH in the crypto market exceeds 50%, and we can categorically claim that the two cryptocurrencies are dominant.

Their changes determine the behaviour of other digital assets. BTC is considered the most crucial cryptocurrency, but its dominance is decreasing. Its market share was more than 80% in January 2017, but by January 2022, it had dropped to around 40%.

The explored periods for BTC and ETH are 17.09.2014-19.01.2024 and 09.11.2017-20.01.2024, respectively. The closing price of cryptocurrencies was studied and predicted, as it reflects sentiment and trading activity at the end of a specific time frame, which is often key for technical analysis.

4. RESULTS AND DISCUSSION

Figure 1 illustrates the preprocessing results for loading a dataset into the machine and algorithm, followed by the visualization of Bitcoin and Ethereum closing prices before training, testing, and prediction.

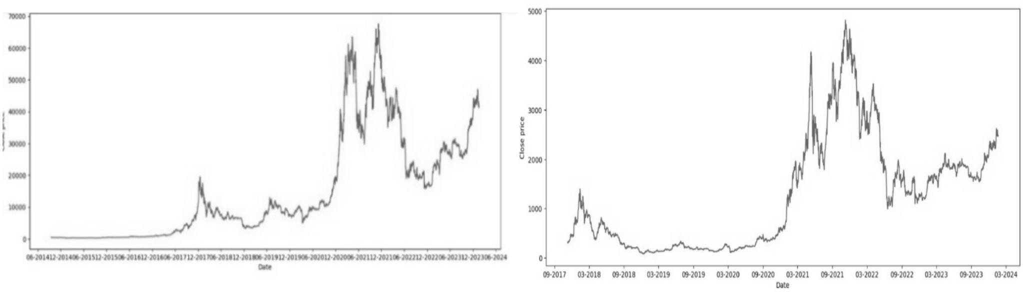

Figure 2. Bitcoin and Ethereum Closing Price Dynamics

In 2017, Bitcoin surged as public awareness of cryptocurrency increased, alongside the emergence of new cryptocurrencies, such as Cardano and Binance Coin. By 2021, over a decade after its debut, Bitcoin remained dominant, with a peak reached on November 5, 2021. The pandemic year marked a pivotal moment, with Bitcoin becoming a hot topic among friends amid record-high prices. In 2021, its value rose due to corporate investments, improvements in the Lightning Network, El Salvador's adoption as legal currency, and Tesla's $1.5 billion purchase announcement. The significance of 2021 in the cryptocurrency sector lies in the increasing corporate investments and initiatives, which drive institutional interest and mass adoption, ultimately leading to regulatory responses. Bitcoin's price fluctuations are linked to the challenges posed by COVID-19, rising inflation, and signals from the Federal Reserve regarding potential interest rate hikes. Following a 75-basis-point increase on June 15, 2022, amid the highest inflation in 41 years in the US, Bitcoin's price fell below $20,500. Thus, both positive and negative news have a significant impact on the price of Bitcoin. Ethereum is the second-largest cryptocurrency by market capitalization, with one coin valued at approximately $4,309.55. Ethereum's all-time high price was $4,800 per coin, recorded in November 2021.

The purpose of time series data analysis is multifaceted. It reveals time patterns that show cryptocurrency price development, including trends, seasonal effects, and anomalies that affect price dynamics. It also serves as a foundation for forecasting models that predict future price movements based on historical patterns. By applying time series techniques, our methodology adapts to the dynamic nature of cryptocurrency markets. Identifying time patterns provides valuable information for recognizing and predicting future price trajectories; hence, time decomposition of cryptocurrencies was applied.

The Min-max scalar technique normalizes Bitcoin and Ethereum's "closing price," which is used to predict their prices. This technique is crucial when working with cryptocurrencies, as their values can fluctuate significantly. After data normalization, a function was developed to prepare input-output sequences from time series containing the prices of the studied cryptocurrencies, which can be used to train a sequence prediction model, such as an LSTM neural network. Through input and output gates, the cell determines which data to store and read, as well as what should be modified. The series is transformed into supervised data. Two models are available in Keras, one of which is a sequential model that works with the functional API and can predict time series. The dense layer is utilized as an external layer for input shapes. The optimized function used is known as the "Adam" optimizer. With this code, the model accepts two parameters: data, which represents time series data, and seq_length, which determines the length of each input sequence. By default, seq_length is set to be equal to 30. It initializes two empty lists, X and Y. List X will contain the input sequences, and list Y will contain the corresponding output values.

Models with distributions (50:50, 70:30, 45:55, 40:60) were tested to find the ideal ratio between training and test sets. The best predictive capabilities appeared at an 80:20 ratio. A validation set is excluded for specific models, aligning with the Pareto principle, which states that about 80% of effects stem from 20% of causes. For the LSTM model, we used 80% of the data for training and 20% for testing accuracy. The network was trained for 20 epochs with a batch size of 64.

Figures 2 and 3 graphically illustrate the relationship between loss and the increasing number of epochs, providing a clear picture of the model‘s training process. During the training process, it is evident that the loss is relatively high at the beginning of training but decreases sharply as the number of epochs increases. This relationship generally reflects that the predicted data is relatively accurate compared to real data.

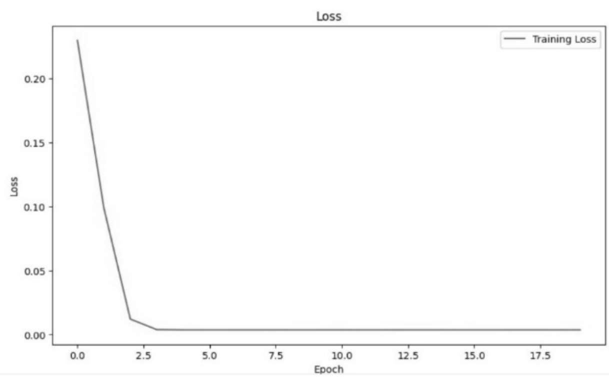

Figure 2. Loss vs. Epoch in LSTM Constructed for Bitcoin Price Prediction

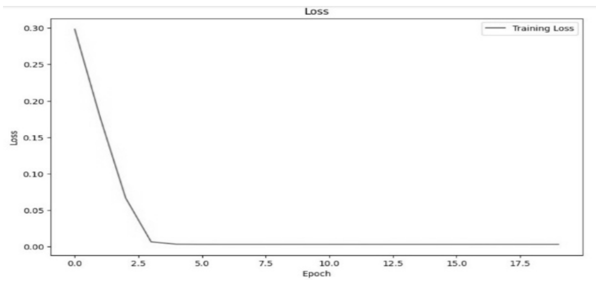

Figure 3. Loss vs. Epoch in LSTM Constructed for Ethereum Price Prediction

The MAE value of 473.03 obtained from the model predicting Bitcoin price shows that, on average, the model's price predictions deviate from actual prices by about $473. This means that the model's predictions on average differ by about $473. The MAE value of 33.77 obtained when predicting the Ethereum price indicates that, on average, the model's predictions differ by approximately $33.77 from actual ETH prices. This means the average magnitude of errors in predictions is $33.77.

The Mean Square Error (MSE) is a vital indicator that measures the average squared difference between the predicted and actual values, reflecting the model's performance. MSE is more sensitive to significant errors than MAE, which calculates absolute differences and better handles outliers by treating all errors equally. The MSE value of 491,268.46 from the model based on BTC closing prices indicates a substantial difference between the predicted and actual BTC prices, indicating significant variability. In comparison, the MSE for the Ethereum model is 2,274.68, suggesting that squared differences between model predictions and actual ETH prices average approximately $2,274.68. This squared value cannot be interpreted directly in ETH price units. The high MSE values may reflect the interconnection between cryptocurrency prices and investor interests.

The RMSE value of 700.91 is the square root of MSE. It provides an interpretable scale for errors. In this case, the RMSE value suggests that, on average, the model's predictions deviate from actual BTC prices by approximately $700. The RMSE value registers a significantly smaller deviation from actual ETH prices, which equals approximately $47.69.

The R^2 result, as already mentioned, represents evidence of our models' explanatory power. This indicator outlines the portion of cryptocurrency variance that our models successfully explain. In the BTC model, the R^2 value of 0.9908 indicates that the model explains approximately 99.08% of the variance in the BTC price data. This is a very high value, close to 1, suggesting the model fits the data well. The model can accurately predict prices, covering 99.08% of price variations. In the developed model aimed at accurately predicting the Ethereum price, the R^2 result of 0.9744 indicates that the model explains approximately 97.44% of the variance in the Ethereum price data. This demonstrates the model's high accuracy in predictions, encompassing significant variations in the data.

In the model constructed to predict BTC prices, the MAPE value is calculated to be approximately 0.018, or 1.8%, suggesting that, on average, the model's predictive capabilities deviate from the actual BTC values by about 1.8%. As noted earlier, lower

MAPE values indicate better accuracy, so a MAPE of 0.018 demonstrates the effectiveness of the developed model. The difference in the MAPE value for the model constructed with an LSTM based on Ethereum prices is minimal, with a value of approximately 0.019, or 1.9% in percentage terms.

In summary, the models demonstrate high results (Table 3) in terms of accuracy (MAE, RMSE) and their ability to explain variance in the studied cryptocurrency price data (R^2). Prediction errors (MAPE) are relatively small, showing that the models can predict future dynamics in the studied cryptocurrency prices.

Table 3. Obtained Results for Used Metrics Regarding LSTM Model Effectiveness

	BTC	**ETH**
MAE	*473.0309049777299*	*33.7658852076863*
MSE	*491268.4580529161*	*2274.6849484694144*
RMSE	*700.9054558590025*	*47.69365731907561*
R^2 score	*0.9907595301434489*	*0.9744027407794406*
MAPE	*0.01803578539885524*	*0.018662714282193626*

In addition to quantitative indicators, Figures 4 and 5 visually summarize the effectiveness of our forecasting models by comparing predicted values with actual cryptocurrency prices. This visual representation offers a clear and intuitive perspective on the efficiency of our models in capturing the nuances of cryptocurrency price movement. The predicted cryptocurrency price curve accurately reflects most details of real price dynamics and matches their trend.

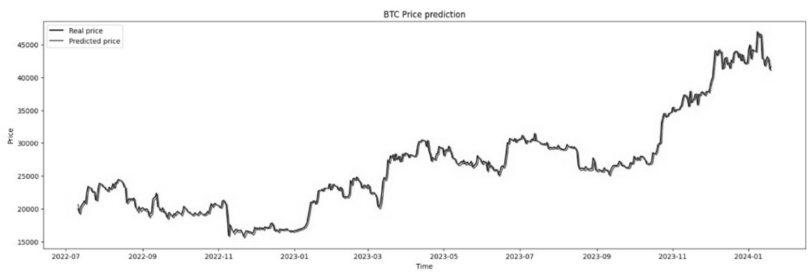

Figure 4. Bitcoin Price Dynamics and Predicted Price for the Period

Figure 5. Ethereum Price Dynamics and Predicted Price for the Period

Based on the applied LSTM algorithm and the obtained quantitative metrics, a relatively small but more predictive capability is revealed regarding the Bitcoin price compared to the Ethereum price. When forecasting the upcoming 30-day period (Figure 6), we confirm that the trend of interconnection between the two cryptocurrencies is expected to be maintained.

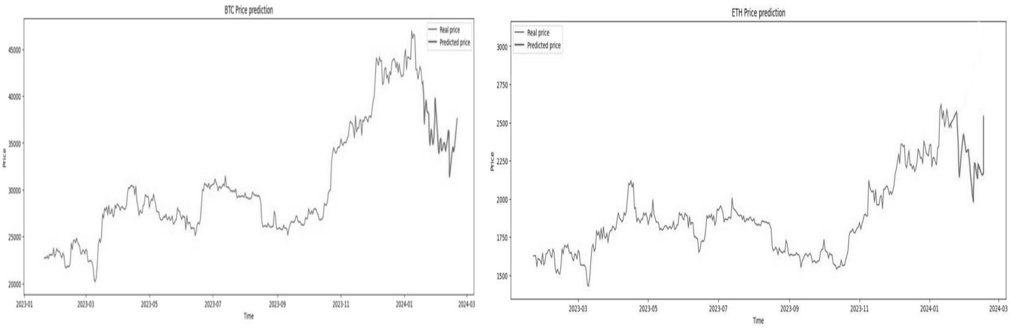

Figure 6. 30-Day Bitcoin and Ethereum Price Forecast

5. CONCLUSION

This research establishes LSTM neural networks as effective tools for cryptocurrency price prediction, contributing significantly to artificial intelligence and the digital economy. The study shows that properly configured LSTM models achieve exceptional predictive accuracy, outperforming traditional forecasting methods.

The methodological contribution of this research centers on the development and validation of optimized LSTM architectures designed explicitly for predicting cryptocurrency prices. Additionally, the study introduces a sequential data transformation methodology specifically tailored for time series analysis of cryptocurrencies, providing a robust framework for handling the unique characteristics of digital asset markets.

The empirical contribution demonstrates superior performance metrics through comprehensive validation across extensive historical datasets. The Bitcoin model achieved remarkable results with an R^2 value of 99.08% and MAPE of 1.8%, establishing near-perfect variance explanation capabilities. Similarly, the Ethereum model demonstrated robust predictive capabilities, with an R^2 of 97.44% and a MAPE of 1.9%. These results represent significant improvement over traditional statistical methods in capturing non-linear price patterns and have been validated across multiple market cycles and volatility conditions, demonstrating the models' reliability under diverse market circumstances.

From a practical perspective, this research develops reliable forecasting tools that provide accurate short-term price predictions to support investment decisions. The models demonstrate visual validation of their effectiveness through close alignment between predicted and actual price movements, while maintaining 30-day forward prediction capabilities with consistent trend patterns.

The theoretical contribution advances AI applications in financial markets by demonstrating the superiority of LSTM in handling sequential cryptocurrency data and establishing performance benchmarks for future cryptocurrency prediction research. This work makes a significant contribution to the understanding of deep learning applications in volatile financial markets and provides a foundational methodology for the development of intelligent trading systems. The study bridges the gap between theoretical AI capabilities and practical financial market applications, establishing new paradigms for analyzing digital assets.

The research demonstrates that LSTM neural networks can effectively capture the complex patterns and long-term dependencies inherent in cryptocurrency price movements, offering reliable forecasting capabilities that significantly surpass traditional statistical approaches. The achieved accuracy levels exceeding 97% for both cryptocurrencies, combined with minimal prediction errors below 2%, demonstrate the practical viability of AI-driven cryptocurrency price prediction for real-world applications.

These findings have significant implications for multiple stakeholders in the cryptocurrency ecosystem. Individual investors can leverage data-driven insights to inform their market timing decisions, while financial institutions can integrate these models for risk assessment and portfolio optimization. Regulatory bodies gain valuable tools for understanding market dynamics and policy formulation, and researchers have a validated foundation for developing more sophisticated AI-driven financial forecasting systems.

The research conclusively demonstrates that LSTM neural networks represent a paradigm shift in cryptocurrency price prediction, offering unprecedented accuracy and reliability for navigating the complex and volatile cryptocurrency landscape. This establishes a new standard for AI applications in digital asset markets, providing essential tools to support informed decision-making in the rapidly evolving digital economy. Future research directions should focus on incorporating additional market indicators, extending prediction horizons, and developing ensemble models that combine multiple AI approaches to enhance prediction accuracy and market coverage further.

ACKNOWLEDGEMENT

The study was conducted as part of the project "Exploring the new trilemma in post-pandemic Europe: artificial intelligence—digital economy—economic development" (ArtInDIGECDevelopment), which is financed under contract No. КП-06-ПН85/34 (BG-175467353-2024-11-0240-C01). The Scientific Research Fund supported the project as part of the Competition for Funding Fundamental Scientific Research – 2024.

REFERENCES

[1] Pahwa, N., Khalfay, N., Soni, V., Vora, D. Stock prediction using machine learning a review paper. *International Journal of Computer Applications*, vol.163, no.5, 2017, pp.36-43.

[2] Peng, Y., Albuquerque, P.H.M., de Sa, J.M.C., Padula, A.J.A., Montenegro, M.R. The best of two worlds: Forecasting high frequency volatility for cryptocurrencies and traditional currencies with support vector regression. *Expert Systems with Applications*, vol. 97, 2018, pp. 177-192. https://doi.org/10.1016/j.eswa.2017.12.004b

[3] Derbentsev, V., Matviychuk, A., Soloviev, V.N. Forecasting of cryptocurrency prices using machine learning. In book *Advanced Studies of Financial Technologies and Cryptocurrency Markets*, Springer: Berlin/Heidelberg, Germany, 2020, pp. 211-231.

[4] Chowdhury, R., Rahman, M. A., Rahman, M. S., Mahdy, M. R. C. An approach to predict and forecast the price of constituents and index of cryptocurrency using machine learning, *Physica A: Statistical Mechanics and its Applications*, Elsevier, 2020. vol. 551(C).

[5] Phaladisailoed, T., Numnoda, T. Machine learning models comparison for Bitcoin price prediction. In *Proceedings of 2018 10th International Conference on Information Technology and Electrical Engineering: Smart Technology for Better Society, ICITEE 2018,* IEEE, 2018, pp. 506–511.

[6] Mangla, N., Bhat, A., Avarbratha, G., Bhat, N. Bitcoin price prediction using machine learning. *International Journal of Information and Computer Science*, vol.6, issue 15, 2019, pp. 318-320.

[7] Qiutong G., Shun L., Qing Y., Zhiyang F. MRC-LSTM: A hybrid approach of multi-scale residual CNN and LSTM to predict bitcoin price, 2021. *Papers 2105.00707, arXiv.org.*

[8] Awoke T, Rout M, Satapathy S, Mohanty L. Bitcoin price prediction and analysis using deep learning models. *In Communication Software and Networks: Proceedings of INDIA 2019*. Singapore: Springer Singapore; 2020. p. 631–40.

[9] Zhou, Q. Price prediction of bitcoin based on LSTM model. In *Proceedings of the 2022 International Conference on Big Data, Blockchain and Economy Management (ICBBEM 2022),* 2023, pp. 255-261, https://doi.org/10.2991/978-94-6463-030-5_27

[10] Chen, Z., Li, C. and Sun, W. Bitcoin price prediction using machine learning: An approach to sample dimension engineering, *Journal of Computational and Applied Mathematics*, vol. 365, 2020, 112395, https://doi.org/10.1016/j.cam.2019.112395

[11] Saad, M., Choi, J., Nyang, D., Kim, J., Mohaisen, A. Toward characterizing blockchain-based cryptocurrencies for highly accurate predictions, *IEEE Systems Journal*, vol. 14, no. 1, 2020, pp. 321-332, https://doi.org/10.1109/JSYST.2019.2927707

Information about the authors:

Mariys Paskaleva is Associate Professor, Ph.D. at the SWU "Neofit Rilski" - Blagoevgrad, Faculty of Economics. She began her research and teaching career at the Faculty of Economics of SWU "Neofit Rilski", Department of Finance and Accounting. Her research interests are in the field of risk management and financial markets.

Manuscript received on 27 May 2025