ITM Web of Conferences **68**, 01022 (2024) https://doi.org/10.1051/itmconf/20246801022
ICAETM 2024

A comprehensive study on comparison of Long short-term memory, Support Vector Machine, and their hybrid model performance using erratic cryptocurrency data

[1]Bhumika Prakash Hegde, [2] Roopa U

[1]*Department of Management Studies* ,Dayananda Sagar College of Engineering
Banglore, India
[2]*Department of Management Studies* ,Dayananda Sagar College of Engineering
Banglore, India

Abstract

Prediction of relatively accurate cryptocurrency prices remains a big challenge due to the high volatility inherently associated with it and the absence of appropriate valuation metrics. This research explores the performance of Long Short-Term Memory (LSTM), Support Vector Machine (SVM), and the hybrid model of these two algorithms for this complex task. LSTM has demonstrated significant potential in capturing short-term price fluctuations. At the same time, the hybrid model aims to combine the strengths of temporal dependencies of LSTM, and nonlinear data pattern recognition of SVM considering the generalization ability of the models, robustness, computational efficiency, and interpretability. To evaluate the models' performance, a comprehensive evaluation framework was used. Historical daily price data for five leading cryptocurrencies had been used. This data had been used to test the performance of algorithms used in this study, by using metrics such as R-Square value and P value, Root Mean Square Error (RMSE) and Mean Absolute Error (MAE). This research aims to provide comparative analysis of machine learning and deep learning models for the cryptocurrency price forecasting. The insights/outcomes gained by this study holds value for both forecasters and researchers. Upcoming studies can focus to explore more advanced hybrid architectures by adding additional data sources and checking how varying market conditions affects model performance.

Keywords— *Cryptocurrency, Hybrid Model, LSTM, SVM, Model Evaluation.*

I. Introduction

Cryptocurrencies are digital form of currency which has got high popularity over recent years, gaining new developments in the financial market. Bitcoin has been introduced in 2009, ever since that, the cryptocurrency market has seen constant growth, which has led to the creation of various other cryptocurrencies (Albayati et al., 2020). Some of the popular cryptocurrencies are, Bitcoin, Ethereum, Solana, BNB, and Tether. These virtual currencies use the technology of blockchain which makes sure that transactions that occur virtually are made secure, irreversible once completed and are also transparent (Lotfi et al., 2021). Even though the virtual currencies have all these advantages the market fluctuates highly and suddenly with the prices often rapidly moving up and down within very small time frame. This high volatility of cryptocurrencies which is unavoidable makes the forecasting challenging for financial analysts , investors and researchers.

Prediction of prices of these currencies and their rapid movements in the cryptocurrency markets is needed for making good investment decisions and also for risk evaluation that may come suddenly and developing effective trading strategies. Financial models such as traditional models (ARIMA etc) are present to forecast the prices they struggle to predict prices in highly volatile suddenly changing market condition. To overcome this problem machine learning (ML) and deep learning models are useful. There are many algorithms among which Long Short-Term Memory (LSTM) and Support Vector Machines (SVM) have shown good outcomes because of their ability in manging time series data and non-linear relationships within the data respectively.

LSTM is a type of Recurrent Neural Network (RNN) and it is particularly well performed for forecasting of time series data because it has the capability to handle long-term dependencies which are present in the data (Li et al., 2020). LSTM models are used in several applications which includes: price prediction, speech-text analysis, and forecasting of stock market prices. Their ability to learn and understand temporal patterns and dependencies makes them well chosen for cryptocurrency prices forecasting by taking the historical data. SVM is a supervised machine learning technique which is used for tasks of data classification and regression. SVM has performed well in high-dimensional data handling and it is known for strong non-linear relationship management by using various kernel functions. Even though SVM has shown good performance in financial forecasting its ability in the cryptocurrency markets which is highly erratic remains unclear (Bouoiyour, J., & Selmi, R. 2021).

Some of the previous researches suggest that LSTM and SVM models have the ability in digital currency prices forecasting a comprehensive comparative analysis has not been made yet (Li et al., 2020). Additionally the advantages of merging these models into a hybrid model which could enhance the strengths of both the stand alone algorithms remains unexperimented and unexplored. The aim of this study is to measure and evaluate the performance of LSTM, SVM, and their hybrid. The hybrid model which is proposed, is to improve accuracy of prediction by combining LSTM's ability of temporal dependencies with SVM's capability of strong classification.

II. Literature Review

A. Deep Learning Models in Forecasting and Prediction Tasks

Aim of this section is to explore how well Long Short-Term Memory, Support Vector Machine and their hybrid model might be able to predict the erratic cryptocurrency price. Many researchers have made a deeper study in many different fields, which provides us with a solid foundation to understand the working pattern and ability of these algorithms. Some of the studies may not be directly related to the cryptocurrency price prediction but they do provide different perspectives and helps in better understanding of the algorithms.

B. Hybrid Models: Combining LSTM with Other Architectures

These days, to improve the prediction accuracy LSTM is combined with other models. For example, to predict short-term water quality CNN-LSTM hybrid model was used (Barzegar et al.,2020). This model has shown a good performance by resulting in low error rates and a considerable quick training period. These results indicate that the hybrid models may perform better in rapidly changing environments rather than the stand alone models. Another hybrid approach was built i.e Conv-LSTM model by (Zheng et al.,2021) . This model uses attention mechanisms which helps to predict flow of traffic over short periods. The results from this was didn’t only show the high accuracy but it also showed the fast processing ability of the model. From these studies it is evident that combination of model/algorithms can improve the prediction results for data which require temporal as well as spatial understanding. Hybrid model also shown a good result in the field of environmental science. (Li et al.,2020) A CNN-LSTM model was built to predict PM2.5 air pollution levels which very well in providing improved accuracy. (Tian et al.,2018) A similar study was conducted where LSTM was integrated with Convolutional Neural Networks for the purpose of short-term prediction. This study was able to show that the integration with neural networks helps to enhance the predictive power of the built models. This concept is not only limited to environmental data but also for all time series data. (Kavitha et al.,2021) A hybrid model was crafted to predict heart disease and outcome of this pointed out how blending algorithms or models can improve preferred results rather than a using a single one.
From all the above stated studies, it is clear that the hybrid models do have the potential to improve the prediction accuracy. These insights are taken as a basis to create the hybrid model of SVM and LSTM.

C. LSTM Models: Superior in Time-Series Prediction

LSTM models are good in time-series forecasting because they are have the ability to understand the long-term dependencies within the time series data. Ability of LSTM in predictive tasks was highlighted by (Sherstinsky.,2018) where he stated that LSTM is a strong choice across many predictive tasks. For example predicting the intensions of online shoppers was successful by using LSTM (Sakar et al.,2018). This signifies decision-making process of LSTM. State Refinement for LSTM (SR-LSTM) was made by (Zhang et al.,2019). This aim of this study was to refine the prediction of pedestrian trajectory. In this experiment, internal states of LSTM were studied deeply where paying attention to the thinking process of the model can make it more accurate. (Xiang et al.,2020) An LSTM model was used for the prediction of rainfall and runoff patterns. This study helps to understand that LSTM are good in handling time series data. All these studies provide insights that LSTM has natural ability in managing time-series data.(Zhou et al.,2019) An innovative step was taken in forecasting the short-term photovoltaic power by attention mechanism introduction to the model hence resulted in performance boost. (Qiu et al.,2020) extended this idea to stock price prediction.

D. SVM Models: Effective Predictive Maintenance

Support Vector Machines are popular in many sectors such as finance, healthcare, energy and economics. A study by (Kurani et al.,2021) compared the performance of SVM with Artificial Neural Networks for the purpose of stock price forecasting. They found that SVM excelled in predicting financial trends which is very important in financial forecasting. That quality of SVM makes it a choice for forecasting in financial market data. (Wan et al.,2021) used a semi-supervised SVM model which did support brain image fusion task in digital twin application. This study is unrelated to cryptocurrency but this study talks about the strength of SVM in handling complex data fusion task. Many research supports potential of SVM for stock price forecasting. (Selvamuthu et al.,2019) combined SVM with other machine learning methods to predict stock movements which highlighted the ability and adaptability of SVM in capturing market movements. (Shen and Shafiq.,2020) also found that SVM was good at identifying short-term stock market patterns. (Zhang et al.,2018) SVM was combined with LSTM to predict power systems by combining it with LSTM to improve prediction of line trip faults. This successful integration of SVM and LSTM shows potential to experiment this with time-series forecasting.

E. Comparative Analysis and Research Gaps

Good outcomes have been observed with stand-alone LSTM and SVM models and their hybrid models but several domains within the literature still which exist require further deeper investigation. The performance of LSTM models has consistently shown remarkable accuracy across various forecasting tasks, but their comparative performance in comparison with SVM in the context of cryptocurrency's erratic nature has not been fully investigated and analyzed. Additionally, applying these models specifically to volatile and highly unpredictable cryptocurrency data remains underexplored. Moreover, there is a requirement for research that is focused on developing new hybrid architectures/models that enhance the strengths of both LSTM and SVM. Considering the success of similar hybrid approaches in other domains and scenarios, hybrid models may offer significant and preferable advantages for cryptocurrency data analysis. Future research should aim to validate the effectiveness of LSTM, SVM, and hybrid models across different market conditions where sudden surges and downfalls are common, and data scales to determine the most suitable models for understanding the volatility inherent in cryptocurrency markets.

III. METHODS AND METHODOLOGY

This research adopts a quantitative methodology with an analytical approach to evaluate the effectiveness of machine learning models LSTM SVM and their hybrid model in forecasting cryptocurrency prices. Historical daily price data from 2020 to 2024 for Ethereum, Solana BNB, Tether, and Bitcoin was obtained from Yahoo Finance. The data underwent passing steps including handling missile values, normalization, and division into training and testing with sets for model development. These models were developed and their performance is measured by using Python with the help of essential libraries Pandas, NumPy, Scikit-Learn and Keras etc. To test the performance of these models metrics used are R Square value(R^2), Root Mean Square Error (RMSE), Mean Absolute Error (MAE) and P values. The analysis made has maintained proper train-test splits and has also made sure of data integrity and applied techniques like regularization and normalization has been done to the dataset to reduce bias which may present in the dataset. For objectivity and adaptability, a quantitative approach had been chosen and advanced models were selected to handle time series and non-linear data. This study gives valuable perception it also suggests evident areas for future and further research and experimentation.

IV. DATA ANALYSIS

A. Hypothesis

Null Hypothesis (H_0): No significant difference is present in the R-Square values among the different algorithms used for each of the selected cryptocurrencies.

Alternative Hypothesis (H_1): A significant difference is present in the R-Square values among the different algorithms used for each of the selected cryptocurrencies.

The above-stated hypothesis has been formulated to measure the statistical significance of the performance of various algorithms in cryptocurrency price prediction. By formulating a null hypothesis that assumes no significant difference and an alternative hypothesis that suggests otherwise, the goal is to objectively determine whether the choice of algorithm affects predictive accuracy as indicated by the R-Square values. This analysis is critical for identifying the most suitable model for cryptocurrency price prediction.

Information of the data.

Data is secondary data and contains information on the daily price of cryptocurrencies such as open, high, low, and close which are generally known as OHLC from 2020 to 2024. It also contains the data of adjusted close and the volume of the stock.

Data is pre-processed and handled for missing values and normalized for the models to understand the data.

Currencies taken into consideration- BNB, Tether, Ethereum, Bitcoin, Solana.

B. Model Performance

TABLE I

Currency	Algorithms	R-Square	P- Value
Ethereum	LSTM	0.9852568	1.95E-280

	SVM	0.9681983	1.10E-229
	Hybrid	0.9812577	1.36E-264
Solana	LSTM	0.9757197	7.32E-204
	SVM	0.9353864	1.02E-150
	Hybrid	0.9651445	3.12E-184
BNB	LSTM	0.9916855	2.999176e-318
	SVM	0.9708234	2.25E-235
	Hybrid	0.9880204	3.86E-294
Tether	LSTM	0.9917217	1.545714e-318
	SVM	0.9708234	2.25E-235
	Hybrid	0.988336	6.66E-296
Bitcoin	LSTM	0.9801917	5.82E-232
	SVM	0.7842884	6.47E-92
	Hybrid	0.9527774	5.09E-181

TABLE 2

Currency	Algorithms	RMSE		MAE	
		Train	Test	Train	Test
Ethereum	LSTM	102.2031748	103.9342713	61.8485252	75.23588094
	SVM	248.5589455	151.0587083	212.7218161	124.6995393
	Hybrid	148.7606806	115.3115203	126.7289609	90.90956817
Solana	LSTM	4.949501335	7.266803622	2.826000639	5.468638612
	SVM	15.87647185	11.38921428	13.95879532	9.265544601
	Hybrid	8.595800536	8.567453543	7.497021118	6.737467024
BNB	LSTM	16.32019777	19.32443493	9.144111015	13.36972931
	SVM	13.36972931	48.40258037	36.2020219	38.65744727
	Hybrid	25.94625362	31.34392386	21.47605936	23.91795186
Tether	LSTM	18.01790658	18.55031211	11.31440946	14.19333611
	SVM	43.91294588	48.40258037	36.2020219	38.65744727
	Hybrid	25.14317431	24.94352369	20.98989098	20.55388634
Bitcoin	LSTM	1706.002796	1155.813077	1826.185732	1350.161305
	SVM	2674.990157	8840.572574	2263.792051	6572.820655
	Hybrid	1946.409057	4593.853687	1567.771321	3524.920746

From the above table, the model performances are inferred as follows: LSTM Model: This model has generally performed the best across most of the cryptocurrencies analyzed, showing high R-Square values alongside low RMSE and MAE, which indicates both efficiency and reliability. For instance, the LSTM model for Ethereum achieved an R-Square of 0.9853, while for Bitcoin, it reached 0.9801.

SVM Model: Compared to both LSTM and hybrid models, SVM models showed lower performance, as reflected in their lower R-Square values and higher RMSE and MAE. For example, the SVM model for Bitcoin had the lowest R-Square of 0.7843 and the highest RMSE at 8840.573.

Hybrid Model**:** This model demonstrated competitive performance, with high R-Square values and statistically significant P-values, often striking a good balance between accuracy and model complexity. Notably, the hybrid model for Tether achieved an R-Square of 0.9834, while for Solana, it was 0.9651.

C. Hypothesis Testing

TABLE 3

ANOVA TEST

SUMMARY

Groups	*Count*	*Sum*	*Average*	*Variance*
LSTM(R ^2)	5	4.9245754	0.98491508	4.9788E-05
SVM(R^2)	5	4.6295199	0.92590398	0.0064923
Hybrid(R ^2)	5	4.875536	0.9751072	0.00024436

ANOVA

Source of Variation	*SS*	*df*	*MS*	*F*	*P-value*	*F crit*
Between Groups	0.009999102	2	0.004999551	2.21008712	0.15234244	3.885294
Within Groups	0.027145814	12	0.002262151			
Total	0.037144916	14				

P-Value (0.1523)**:** The p-value exceeds 0.05, leading to the conclusion that the null hypothesis cannot be rejected. This indicates that there is no statistically significant difference in the mean R-Square values across the three algorithms (LSTM, SVM, Hybrid). In simpler terms, this analysis suggests that none of the algorithms significantly outperforms or underperforms the others in fitting the data.

F-Statistic (2.2101) vs. F crit (3.8853)**:** The F-Statistic of 2.2101 is lower than the critical F-value of 3.8853, indicating that the differences in R-Square values among the algorithms are not statistically significant. Based on this ANOVA analysis, it can be concluded that the R-Square values across LSTM, SVM, and Hybrid models do not differ significantly, implying that all three algorithms perform similarly in explaining the variance in cryptocurrency prices. Therefore, based solely on the R-Square metric, no algorithm can be deemed superior in this context.

D. Study Outcomes

LSTM Model: This model has consistently shown higher R-Square values and lower RMSE and MAE across the selected five cryptocurrencies, indicating robust and good performance in prediction. This suggests that LSTM has the potential in capturing temporal dependencies in cryptocurrency data.

SVM Model: Displayed lower R-Square values and higher error measures compared to LSTM, suggesting it may be less effective in forecasting cryptocurrency prices.

Hybrid Model: Showed mixed results, occasionally outperforming the SVM model but generally lagging behind the LSTM model in terms of R-Square across most cases.

The Ability of generalization: Hybrid model had the RMSE and MAE on the test data which were lower than those on the training data which shows that it has a good ability to generalize the unseen data. This was clearly noticed in case of Ethereum and Solana.

V. FUTURE SCOPE OF STUDY

Experimenting with different other combinations and algorithms to increase and improve the performance of models which can considered as a further improvisation of the study. There are several techniques such as stacking which use the input from all the algorithms used and cascading etc could be used to combine LSTM with SVM more effectively. But enough care should be taken not to introduce more complexity as the models are already complex. One of the possible reasons for the observed low performance of SVM could be the absence of hyperparameter tuning due to limitations of computation. Hyperparameter tuning and feature engineering are essential may enhance the model performance of SVM which in turn improve the hybrid model. Adding more data sources such as market sentiment and macroeconomic indicators might help to further enhance the accuracy of the predictive models. Cryptocurrency prices are heavily affected by the factors mentioned, exploring how those factors impact the prediction may offer deeper perspective. Also measuring the stability of the models under highly challenging market conditions i.e sudden ups and downs is essential for checking their reliability in harsh environments. The model can be further improved by experimenting with different look-back periods for understanding the different patterns in the data and helps to get a better picture.

VI. CONCLUSION

A detailed comparison of LSTM, SVM and their hybrid model for cryptocurrency price prediction has been provide by this study. LSTM consistently giving the most accurate and best reliable forecasts across various cryptocurrencies which taken for experimentation as shown by the results from this study. Hybrid models have performed good when statistical significance and generalization ability are considered. It successfully combines the strengths of both LSTM and SVM. But, SVM model require further optimization and improvement to obtain the better results. The findings point out the importance of advanced machine learning and deep learning techniques like LSTM for accurate prediction of cryptocurrency price and also recognizes the benefits of hybrid models. Users can opt for the models based on their convention and requirement.

REFERENCES

[1] Albayati, H., Kim, S.-K., & Rho, J. J. (2020). The influence of technical, organizational, and environmental factors on blockchain technology adoption: The case of financial and manufacturing firms. *Sustainability, 12*(10), 4035.

[2] Lotfi, A., Pourpanah, F., Arabameri, E., & Mehrabi, H. (2021). A review of machine learning applications in cryptocurrency market forecasting. *Journal of Financial Markets, Institutions & Instruments, 30*(3), 113-142.

[3] Bouoiyour, J., & Selmi, R. (2021). Cryptocurrencies: A survey on efficiency and their empirical relations with financial assets. *Journal of Risk and Financial Management, 14*(3), 141.

[4] Li, X., Zhang, C., Sun, L., & Zhang, M. (2020). A hybrid LSTM-CNN model for predicting short-term air quality in Beijing, China. *Atmospheric Environment, 223*, 117297.

[5] Tian, H., Li, G., Zhang, L., & Zhu, C. (2018). A hybrid model of LSTM and CNN for short-term load forecasting. *Energy, 144*, 549-556.

[6] Kavitha, Dr.M.., Gnaneswar, G.., Dinesh, R.., Sai, Y.., & Suraj, R.. (2021). Heart Disease Prediction using Hybrid machine Learning Model. *2021 6th International Conference on Inventive Computation Technologies (ICICT)* , 1329-1333 .

[7] Barzegar, R., Mosaedi, A., & Toroghi, F. (2020). A hybrid CNN-LSTM deep learning model for short-term water quality prediction. *Water Resources Management, 34*, 4597–4612.

[8] Zheng, Z., Li, X., & Song, H. (2021). Short-term traffic flow prediction with an attention-based LSTM-CNN model. *IEEE Transactions on Intelligent Transportation Systems, 22*(7), 4329-4340.

[9] Sherstinsky, A. (2018). Fundamentals of recurrent neural network (RNN) and long short-term memory (LSTM) network. *Physica A: Statistical Mechanics and Its Applications, 507*, 1-36.

[10] Zhang, L., Fang, L., Wu, H., & Zhou, P. (2019). State refinement for pedestrian trajectory prediction using LSTM. *Sensors, 19*(21), 4689.

[11] Xiang, C., Chen, Y., Zhang, J., & Liu, D. (2020). Rainfall-runoff prediction with a sequence-to-sequence LSTM model. *Journal of Hydrology, 586*, 124866.

[12] Zhou, S., Yang, J., & Fan, C. (2019). Attention-based LSTM neural network model for short-term photovoltaic power forecasting. *Energy, 175*, 454-463.

[13] Qiu, Y., Zheng, H., & Ren, L. (2020). Financial time series forecasting using LSTM networks with attention mechanism. *IEEE Access, 8*, 185991-186001.

[14] Kurani, N., Ramesh, B., & Sundar, M. (2021). Stock price prediction using support vector machine and artificial neural networks: A comparative study. *Journal of Computational Science, 50*, 101322.

[15] Wan, J., Tang, S., & Li, D. (2021). Semi-supervised support vector machine for digital twin-based brain image fusion. *Future Generation Computer Systems, 117*, 397-405.

[16] Selvamuthu, D., Kumar, V., & Mishra, A. (2019). Indian stock market prediction using artificial neural networks on tick data. *Financial Innovation, 5*(1), 1-12.

[17] Shen, Y., & Shafiq, M. O. (2020). Predicting short-term stock market trends using machine learning algorithms. *Journal of Financial Data Science, 2*(3), 33-45.

[18] Yang, Zhang., Ce, Li., & Lian, Li. (2017). Electricity price forecasting by a hybrid model, combining wavelet transform, ARMA and kernel-based extreme learning machine methods. *Applied Energy* , 190 , 291-305 .

[19] Filho, Hugo Crisóstomo de Castro., Júnior, O. C.., Carvalho, O.., Bem, Pablo Pozzobon de., Moura, Rebeca dos Santos de., Albuquerque, Anesmar Olino de., Silva, Cristiano Rosa e., Ferreira, Pedro Henrique Guimarães., Guimarães, R.., & Gomes, R.. (2020). Rice Crop Detection Using LSTM, Bi-LSTM, and Machine Learning Models from Sentinel-1 Time Series. *Remote. Sens.* , 12 , 2655 .

[20] Wan, Zhibo., Dong, Youqiang., Yu, Zengchen., Lv, Haibin., & Lv, Zhihan-han. (2021). Semi-Supervised Support Vector Machine for Digital Twins Based Brain Image Fusion. *Frontiers in Neuroscience* , 15 .