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Determining the Best Activation Functions for Predicting Stock Prices in Different (Stock Exchanges) Through Multivariable Time Series Forecasting of LSTM

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ABSTRACT

LSTM (Long Short-Term Memory) has proven its worth in terms of predicting Stock prices through questioning market conditions. This research focuses on the quality of LSTM predictions when various activation functions are applied within the context of noisy market data. In this research, we have used 25 different stocks from diverse stock exchanges and observed the predictions created by different activation functions such as Relu, Elu, and TanH. Our research would involve this accuracy within the context of average loss accumulation and price predictions for the stock sample. The market conditions will imply the features of similar epoch runs, and the same training and testing period, which are irrespective of SE and LSTM feature parameters defined by market-benefitting suggestions. This research has found an accuracy of 80% through the multivariable prediction method derived from the Hyperbolic Tangent activation function, suggesting that this function is the best for price prediction based on LSTM through the multivariable method.

Keywords: LSTM, SE, Epoch, Feature settings, Train test split, Accuracy, MAE, and RMSE.

INTRODUCTION:

Stock prediction has been an issue of interest for investors since the beginning of an investment-based business. Walter E. Brown defined that among the various alternatives for making investments stocks are the best possible alternatives, which define the lowest volatility but highest possible return (W. E. Brown, 1982). Yu & Yan in their research supported the idea of predicting stocks using a deep neural network which has been highly accurate rather than SVM & random forest regressor (Yu & Yan, 2019). JW Lee has shown that among the various prediction methods, the prediction process that uses reinforcement learning-based forecasting processes has been the most capable in terms of making accurate predictions (JW Lee, 2001). *Nikou et al.* have shown that deep learning-based price prediction algorithms have better prediction quality rather than machine learning-based prediction methods (Nikou *et al.,* 2019). Hence with research suggestions, we can substitute the understanding that deep learning-based prediction processes are suitable for stock price forecasting. It has also been observed that in highly unstable markets like DSE (Dhaka Stock Exchange), LSTM could predict stock prices effectively (Sami *et al.,* 2021). Sami *et al.* also have shown that LSTM is capable of predicting stock prices of stable markets like NYSE (Sami *et al.,* 2021).

In this research, we evaluated the best possible activation functions for which we can predict stock prices with the highest level of accuracy. Farzad *et* *al.* have evaluated among various activation functions sigmoid is the most popular one for prediction (Farzad *et al.,* 2019). Elsayed *et al.* have found that the most popular and effective prediction processes are RELU, ELU, and tanh functions, which have accurate predictions (Elsayed *et al.,* 2018). Rana *et al.* consequently agree with Elsayed's suggestion for effectively using RELU, ELU, and tanh activation functions for predicting stock prices with high accuracy (Rana *et al.,* 2019).

Hence in this research, we are going to evaluate RELU, ELU, and tanh activations functions and their capability to make accurate predictions within the multivariable price parameters.

Literature Review

Campbell & Kyle suggested that noise trading occurs when the market remains highly volatile and such market behavior is prevalent for stock trading (Campbell & Kyle, 1993). In the case of price forecasting, LSTM maintains a feature of exploding and vanishing gradient that helps reduce the noise impact in the case of forecasting. Hence LSTM can be considered as a price prediction method for Stocks (Siami *et al.,* 2019). In terms of selecting stocks of variant markets, it's highly imperative that the activation function chosen should have the best accuracy in terms of price prediction and accuracy. Chunhachinda *et al.* have shown that different stock exchanges in the whole world with variants representing stocks as a background will define the best possible data sample for stocks (Chunhachinda *et al.,* 1997). Haroon & Rizvi have shown how different stock markets have differences in terms of liquidity and easy profit opportunity (Haroon & Rizvi, 2020). Our research will evaluate the competitive quality of activation functions applied in the LSTM process and how these functions will qualify with accurate price predictions. In this research, the liquidity and easy profit opportunity which could be understood through fundamental financial analysis will be compared with statistical evaluations through LSTM. Istiake *et al.* have suggested that in the case of LSTM-based price predictions, it's always better to make the least Epoch runs for more than 35 and till 100 as the loss process remains pretty much the same till 1000 epoch runs because the data becomes noisy (Istiake *et al.,* 2020). But Istiake *et al.* have also shown that at least an epoch run of 35 makes the loss process effective enough for all stock prices. Hence this research is compiled within the framework of more than 50 epoch runs at a minimum for effective predictions of prices. Beyaz *et al.* have shown that in the case of stock price forecasting the ideal training and testing data split should be accompanied by an 80% training dataset (Beyaz *et al.,* 2018). Following this data set split Bloomberg and Goldman Sachs got the best result of price predicttions (Jiang *et al.,* 2017) applied through machine learning parameters defined by the best possible feature settings suggested by predicting stock market conditions. Classification algorithms play a huge role in the selection of stocks in this research. Using K Nearest Neighbor HM Sami success-fully created a portfolio that has selected stocks from NYSE (Sami HM, 2021). Similarly, HM Sami has shown how K Nearest Neighbor has been incredibly qualified enough to make a selection of qualified Human resources (Sami HM, 2021). Chen and Hao also showed that by using the K Nearest Neighbor algorithm with financial ratios as background we can effectively select stocks (Chen & Hao, 2017).

Karaven *et al.* have found the importance of Tanh for making accurate predictions in reference to making weather predictions (Karaven *et al.,* 2020). With multivariable factors in consideration, weather predictions for a specific time slot have a high degree of similarity with noisy stock prices according to the research performed by Karaven. Hence Tanh is considered an important activation function for this research. As financial time series forecasting needs to have implications for both forget gate and output gate, it was found that the integration in both RELU and ELU through multivariable price series of the S & P 500 index can make the most accurate predictions (Borovykh *et al.,* 2018).

Theoretical Background

LSTM (Long Short-Term Memory)

LSTM is a neural network structure that is primarily based on artificial recurrent neural networks and has the sole right to predict the correct prediction phenomenon. It can analyze data sequences due to its network structure. The LSTM unit is made up of a component, an entry gate, an exit gate, and a forgetting gate (Jiang *et al.,* 2017).

(a) Instead of arbitrary time intervals, the unit structure remembers the value structure.

(b) Gates regulate the flow of information into and out of the cell.

The goal of the LSTM organization is to eliminate the gradient problem in order to achieve the best failure solution. The constant flow of input across gradient LSTM units enables the solution method (Wu *et al.,* 2018). Due to the calculation process and the participation of finite precision numbers (rounding errors) in nonlinear time series predictions involving vanilla RNN via backpropagation, RNN continues to use gradients as missing or explosive basic feeds without changes (they tend to be at zero) or infinite change (towards infinity). In general, LSTMs include a forget gate, which allows you to ignore error values propagating backward from the output layer sequentially and slowly cut them through the feed-forward neural network through repetition (Siami *et al.,* 2019). The loop only allows the LSTM to train gradients with weight updates that appear to be valid for future value benchmarks (Alahi *et al.,* 2016). Finally, in terms of precision, the actual weight update reference and gradient growth indicate the propagation factor associated with the time series prediction based on any value of the training and test values.

Activation Functions

ELU (Exponential Linear Unit)

The Exponential Linear Unit (ELU) is a neural network activation function. ELUs, unlike ReLUs, have negative values, allowing them to push mean unit activations closer to zero, similar to batch normalizeation, but with less computational complexity. Because of the reduced bias shift effect, mean shifts toward zero accelerate learning by bringing the normal gradient closer to the unit natural gradient. Although LReLUs and PReLUs have negative values, they do not guarantee a noise-resistant deactivation state. With smaller inputs, ELUs saturate to a negative value, reducing forward propagated variation and information.

$$f(x) = x \text{ if } x > 0$$
$$\alpha(\exp(x) - 1) \text{ if } x \leq 0$$

Tanh

The Tanh (also "tanh" and "TanH") function is another name for the hyperbolic tangent activation function. It is very similar to and even has the same S-shape as, the sigmoid activation function. The function accepts any real value as input and returns values ranging from -1 to 1. The larger the input (more positive), the closer the output to 1.0, whereas the smaller the input (more negative), the closer the output to -1.0.

$$g(z) = \frac{e^z - e^{-z}}{e^z + e^{-z}}$$

RELU (Rectified Linear Unit)

The activation function of the rectifier or ReLU (Rectified Linear Unit) is defined as the positive part of its argument

$$g(z) = \max(0, z)$$

The rectified linear activation function, abbreviated ReLU, is a piecewise linear function that outputs the input directly if it is positive; otherwise, it outputs zero. It has become the default activation function for many types of neural networks because it is easier to train and often results in better performance. To train deep neural networks using stochastic gradient descent with backpropagation of errors, an activation function that looks and acts like a linear function but is actually a nonlinear function that allows complex relationships in the data to be learned is required. In addition, the function must be more sensitive to the activation sum input and avoid oversaturation.

METHODOLOGY:

The activation function is the first step in the RNN process in general. Using the activation function, the weighted sum of input is converted into an output from a node or nodes in a network layer. The symbol a<t> represents the activation function. The output function refers to the previous time step's output, which is based on the input x<t>, and activation function a<t>, which is based on the previous time instance's input and activation function values, x<t-1> and a<t1>. Y<t> represents the output based on the input at that time step x<t>. It is critical that all of the following options function properly for the activation functions to produce output.

$$W_{ax}, W_{aa}, W_{ya}, b_a, b_y$$

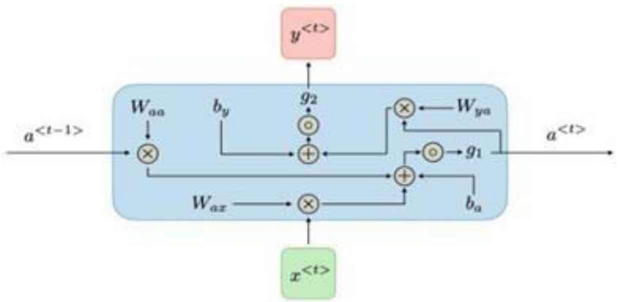
All of these parameters affect the RNN structure, which is used to produce the following results:

$$\boxed{a^{<t>} = g_1(W_{aa}a^{<t-1>} + W_{ax}x^{<t>} + b_a)}$$

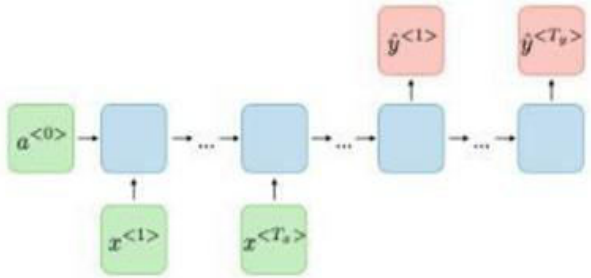
The activation function's bias is related to the activation function's weight allocation of Wax for input and Waa for the activation function. Similarly, for the output activity:

$$\boxed{y^{<t>} = g_2(W_{ya}a^{<t>} + b_y)}$$

The resulting activation is linked to the output bias factor and the output allocated weights, which are represented by Wya. It is related to bias and market factor g1 for price prediction, while g2 remains the activation functions that take effect one after the other. Because of all of these functions, the recurrent network is effective. As a result, the RNN unit as a whole is defined as



Whereas each time step motion allows for successful training based on the data generated by the network. Each of these processes exemplifies the positive aspect of the previous asset price and its relationship to the current asset price.



As many examples as possible would be incurporated into this feed-forward neural network system to train the information to acquire appropriate information in response to situational developments. The RNN design allows biased conditional methods to be completely reliant on the training process. Bias is the most important factor in price prediction because each stock is related to the market via beta but also has its own performance capacity (Stosic *et al.,* 2019). The LSTM process employs a variety of gated structures, such as those shown below. The RNN design allows biased conditional methods to be completely reliant on the training process. Bias is the most important factor in price prediction because each stock is related to the market via beta but also has its own performance capacity (Stosic *et al.,* 2019). The LSTM process employs a variety of gated structures, such as the ones listed below:

$$\Gamma_u \; \Gamma_r \; \Gamma_f \; \Gamma_o$$

Represent the gate notation in the RNN procedure. The symbols above represent the update, relevance, forget, and output gates. As a result, the gates enable the recall of features for price prediction or the obliteration of data for price prediction. The following function shows how gates are linked:

$$\boxed{\Gamma = \sigma(Wx^{<t>} + Ua^{<t-1>} + b)}$$

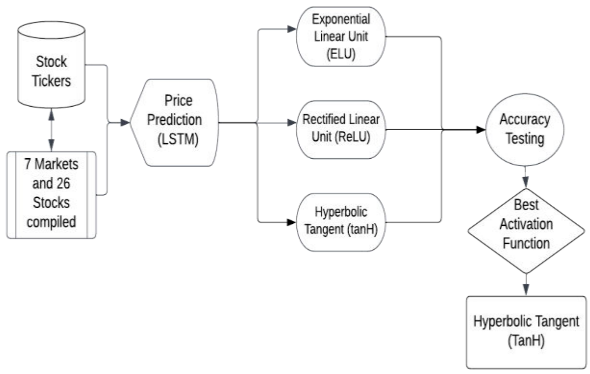
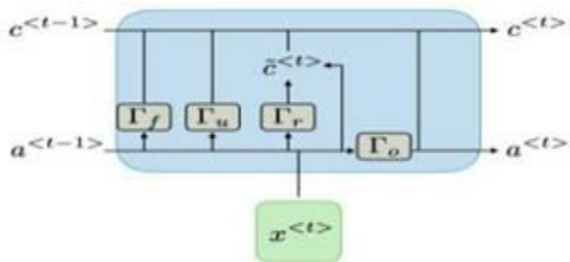


Fig. 1: Illustration of the research process.

Application through LSTM



When used in conjunction with RNN, LSTM is discovered to also have multiple gates within the processing unit. As a result, the goal of LSTM is to aid in the development of effective evaluation and training solutions that aid in: As a result, the goal of LSTM is to aid in the development of effective evaluation and training solutions that aid in the output values that would aid the activation functions for future values are highlighted using RNN trimmed techniques to intentionally manage the exploding gradient problem, as RNN encounters both exploding gradient and vanishing gradient problems. By preserving parallel processing during the boundary line looping process, RNN decreases the risk of infinite. Although RNN can solve the exploding gradient problem, it cannot solve the vanishing gradient problem. When we look at the gated structure of the RNN unit in the LSTM, we can see that it has four gates. C<t> includes a primary output function. Relevance gates are linked to previous activation functions and current input. The situational bias is used to enhance the effectiveness of the primary output in conjunction with the activation functions, which are for the purpose of this research, ReLU, tanh, and ELU.

$$\tanh(W_c[\Gamma_r \star a^{<t-1>}, x^{<t>}] + b_c)$$

In the case of the final output function c<t>, the primary output associated with the update gate structure and the forget gate model will be added to the previous output to determine whether any required information is supposed to be remembered or not so that we can make the prediction process much more efficient. The vanishing gradient problem is eliminated because of this gated feature.

$$\Gamma_u \star \tilde{c}^{<t>} + \Gamma_f \star c^{<t-1>}$$

Furthermore, because the activation function remembers which essential information is required for the prediction process at each phase of the final output, this procedure makes the activation function for the following stage very efficient.

Epochs for Loss Reduction

When the prior step in an RNN supplies irrelevant information to the forward step, the loss function is designated as the loss occurrence jurisdiction during the training process. We can see here that if the main output has less loss than the final output, then the prior information should be used in the feed-forward process. Because LSTM wants to employ its gated structure approach to achieve the precise step of loss reduction, the loss in terms of predictions has been decreed with successful training. As seen in our enlarged Epoch computation, the epoch of 50 - 100 has produced effective forecasts for the procedure to be successful with favorable data. This Epoch is suggested through scholarly suggestions.

$$\boxed{\mathcal{L}(\hat{y}, y) = \sum_{t=1}^{T_y} \mathcal{L}(\hat{y}^{<t>}, y^{<t>})}$$

Back propagation Method

In order to make the financial price forecasting issue suggestively good with respect to time-based propagations, the derivative of loss L concerning matrix W must be updated about each time step. When the relevant information is updated and transferred via the activation stages, the corresponding weights that will be used to predict the price will be altered in each step, according to the findings.

$$\boxed{\frac{\partial \mathcal{L}^{(T)}}{\partial W} = \sum_{t=1}^{T} \left.\frac{\partial \mathcal{L}^{(T)}}{\partial W}\right|_{(t)}}$$

It's been proven that using LSTM's observation stages and feed forwarding method, the loss function for large datasets may be reduced over time. The loss does not become greater if we try taking the same number of training steps on smaller datasets. Furthermore, it has been discovered that smaller datasets and shorter training stages result in lower losses.

RESULTS AND DISCUSSION:

In this research, we have made evaluations of various stocks of Bangladesh, Thailand, India, Malaysia, Japan, and Indonesian SEs. This research focuses to find the accuracy of LSTM through various activation functions where each predicted price output is compared in terms of accuracy. Through this research method, we have accumulated that ELU makes the best possible accuracy among the three different activation functions in comparison to the other method within similar LSTM parameters. Our research has observed a complete finding of 80% accuracy in terms of predicting stock prices with tanH (Hyperbolic Tangent) in comparison to ELU and ReLU which makes prediction comparably at 72% and 48% on average for these stocks.

We have found that ReLU has provided the least amount of positive output. As the accuracy seems widely accepted in most of the stocks of variant SEs then LSTM could considerably be used as an important TSF (time series fore-casting) method widely used by financial organizations to predict future prices of assets. Similarly, the emphasis on classification through segregation is observed in predicting qualified customers with judgmental feature sets defined by acceptable criteria for selecting loan-providing customers by the Naïve Bayes classifier (HM Sami *et al.,* 2021). Similarly, classifying the predicted results in terms of accuracy is also performed here to find the best possible activation function to predict stock prices.

Table 1: Prediction accuracy using different activation functions.

Stock Exchange	Asset Name	Did Price match with next 5 days (YES=1 , NO=0)			
		ELU	ReLU	TanH	Stock Prediction Effectivity
DSE	BDCOM	0	1	1	67%
	BEXIMCO	0	0	0	0%
	ORIONPHARM	1	0	1	67%
	AAMRATECH	1	0	1	67%
HKEX	2269.HK	1	0	1	67%
	2196.HK	0	0	0	0%
	0182.HK	1	1	1	100%
BSE	DIVISLAB	1	0	1	67%
	LTI	1	0	1	67%
	SUNPHARMA	1	0	1	67%
	TCS	1	1	1	100%
JKSE	ERAA.JK	1	1	1	100%
	MERK.JK	1	1	1	100%
	SIDO.JK	1	0	1	67%
JPX	ALPMY	1	1	1	100%
	CHGCF	1	1	1	100%
	DSNKY	1	1	1	100%
	TAK	1	0	0	33%
KLSE	AHEALTH	0	1	0	33%
	INARI	0	0	1	33%
	KOTRA	1	1	1	100%
SET	JMART.BK	0	0	1	33%
	KCE.BK	0	1	1	67%
	SKR.BK	1	1	0	67%
	VIH.BK	1	0	1	67%
Total Yes response from the activation functions		**18**	**12**	**20**	**Average effectivity**
					67%

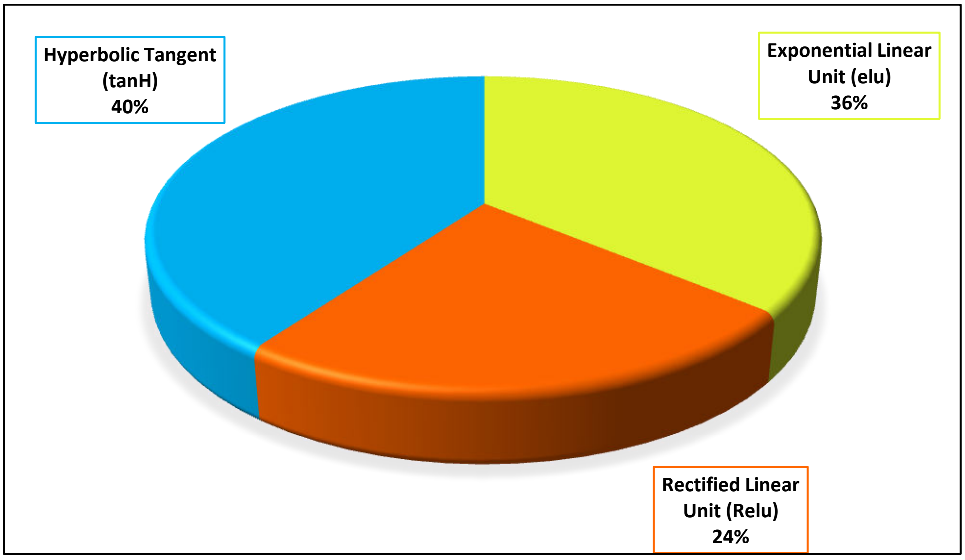
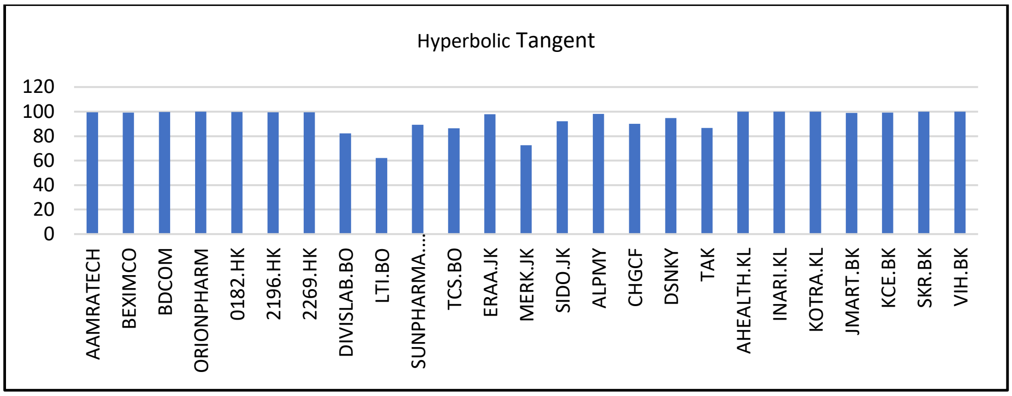
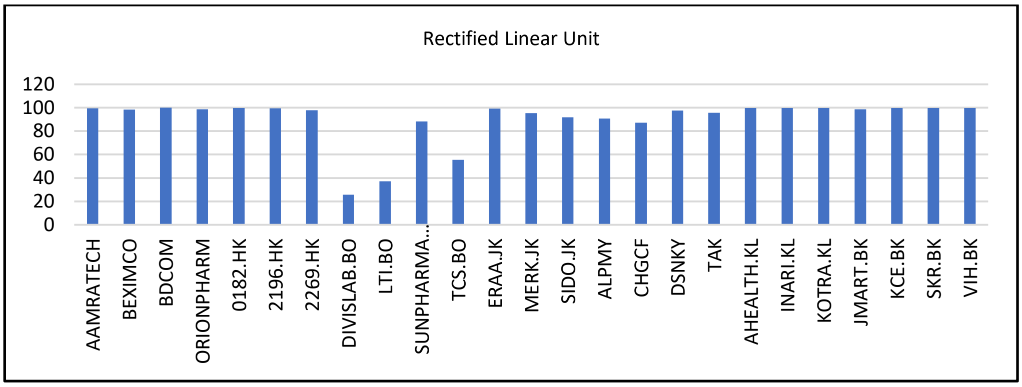
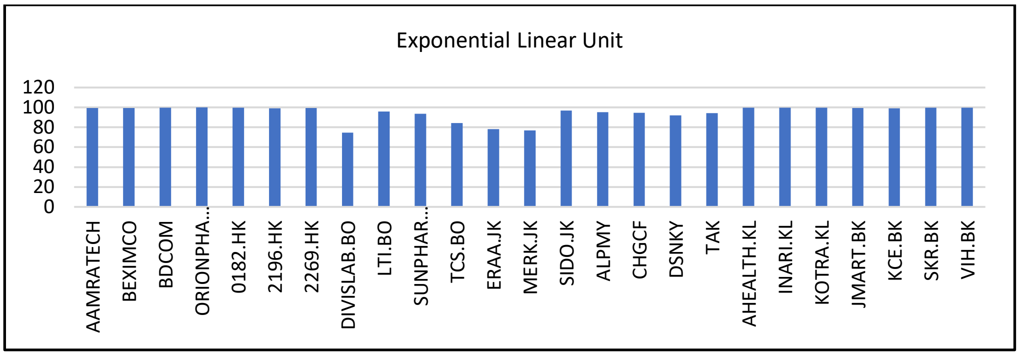


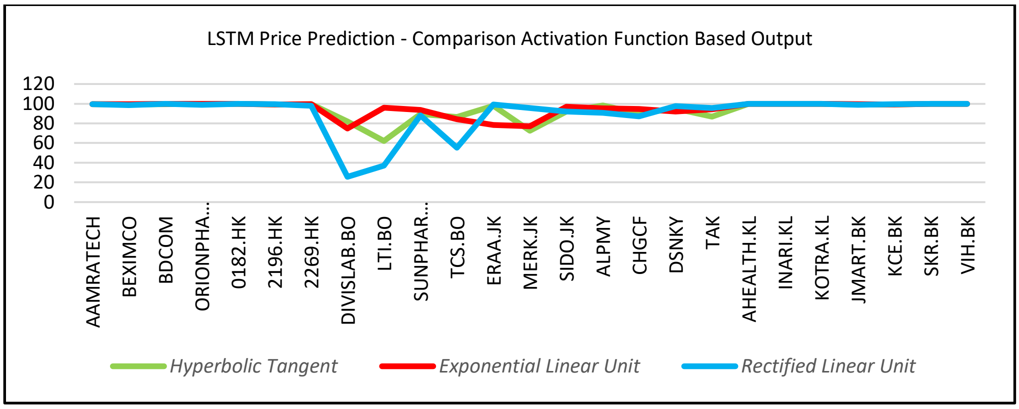
Fig. 2: Illustration of the accuracy of each activation function.

Moreover, we have found that using the same parameter of activation functions in terms of epochs of 50 - 100, the loss starts getting reduced at 10 onwards and remains extremely low till 20 which shows that by scholarly suggestions we make effecttive predictions of stock prices.









Drawbacks & Further improvements

In this research, we did not make predictions based on standard market practices suggested by Wall Street or other major trading organizations' target processes but rather through scholarly suggestions. Through this process, we have not yet evaluated stock price predictions based on market practicing parameters. Moreover, we did not make selections of assets within the parameter of market implications but with random selection processes. Through this process, although we made incredibly good predict-tions, we found that nearly 60% of the assets that we selected showed negative growth. So, our prediction method needs to rely more on financial benchmarks.

CONCLUSION:

LSTM is a strongly suggested method that strengthens the time series-based forecasting method, especially for financial asset pricing. The findings from our research show an average of 67% accuracy of prices in terms of financial pricing. Moreover, it has also been observed that tanH as an activation function is the most effective function to make accurate predictions of prices with an accuracy rate of above 80%. Hence by evaluating stocks of different stock exchanges and different market parameters based on similar training and testing of dataset split, similar epoch runs, similar time frames for test choice, and similar LSTM feature sets, we can justify tanH as the best possible activation function that makes the best possible accuracy selections of assets in terms of prediction of prices.

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CONFLICTS OF INTEREST:

All authors declare that they have no conflicts of interest with the contents of this research work.

REFERENCES:

1) Alahi *et al.* (2016). Social LSTM: Human Trajectory Prediction in Crowded Spaces. *IEEE Conference on Computer Vision and Pattern Recognition (CVPR), 27-30 June 2016, Las Vegas, NV, USA*.
2) Beyaz, E., Tekiner, F., Zeng, X., & Keane, J. (2018). Comparing Technical and Fundamental Indicators in Stock Price Forecasting. 2018 IEEE 20th International Conference on High Performance Computing and Communications; *IEEE 16th International Conference on Smart City; IEEE 4th International Conference on Data Science and Systems*.
3) Borovykh, Anastasia, Bohte, Sander Oosterlee, and Cornelis W., (2018). Dilated Convolutional Neural Networks for Time Series Forecasting, **25**, *J. of Computational Finance*, Forthcoming, Available at SSRN: https://ssrn.com/abstract=3272962
4) Campbell, J. Y., & Kyle, A. S. (1993). Smart Money, Noise Trading & Stock Price Behavior. *The Review of Economic Studies*, **60**(1), 1. https://doi.org/10.2307/2297810
5) Cao *et al.* (2018). Financial time series forecasting model based on CEEMDAN and LSTM. *Physica A: Statistical Mechanics & Its Applications*, **519**, 127-139. https://doi.org/10.1016/j.physa.2018.11.061
6) Chen, Y., & Hao, Y. (2017). A feature weighted support vector machine and K-nearest neighbor algorithm for stock market indices prediction. *Expert Systems with Applications*, **80**, 340-355. https://doi.org/10.1016/j.eswa.2017.02.044
7) Chunhachinda, P., Dandapani, K., Hamid, S., & Prakash, A. J. (1997). Portfolio selection & skewness: Evidence from international stock markets. *J. of Banking & Finance*, **21**(2), 143-167. https://doi.org/10.1016/s0378-4266(96)00032-5
8) Elsayed, N., Maida, A. S., & Bayoumi, M. (2018). Empirical Activation Function Effects on Unsupervised Convolutional LSTM Learning. 2018 IEEE *30th Inter. Conference on Tools with Artificial Intelligence (ICTAI).* https://doi.org/10.1109/ictai.2018.00060
9) Farzad, A., Mashayekhi, H., & Hassanpour, H. (2017). A comparative performance analysis of different activation functions in LSTM networks for classification. *Neural Computing and Applications*. https://doi.org/10.1007/s00521-017-3210-6
10) Haroon, O., & Rizvi, S. A. R. (2020). Flatten the Curve and Stock Market Liquidity - An Inquiry into Emerging Economies. *Emerging Markets Finance &Trade*, **56**(10), 2151-2161. https://doi.org/10.1080/1540496x.2020.1784716
11) Istiake Sunny, M. A., Maswood, M. M. S., & Alharbi, A. G. (2020). Deep Learning-Based Stock Price Prediction Using LSTM and Bi-Directional LSTM Model. 2020 2nd Novel *Intelligent and Leading Emerging Sciences Conference (NILES*). https://doi.org/10.1109/niles50944.2020.92579
12) Jae Won Lee. (2001). Stock price prediction using reinforcement learning. ISIE 2001. 2001 IEEE International Symposium on Industrial Electronics Proceedings (Cat. No.01TH8570). https://doi.org/10.1109/isie.2001.931880

13) Karevan, Z., & Suykens, J. A. K. (2020). Transductive LSTM for time-series prediction: An application to weather forecasting. *Neural Networks*. https://doi.org/10.1016/j.neunet.2019.12.030
14) Nikou, M., Mansourfar, G., & Bagherzadeh, J. (2019). Stock price prediction using DEEP learning algorithm and its comparison with machine learning algorithms. Intelligent Systems in *Accounting, Finance & Management*. https://doi.org/10.1002/isaf.1459
15) Rana, M., Uddin, M. M., & Hoque, M. M. (2019). Effects of Activation Functions and Optimizers on Stock Price Prediction using LSTM Recurrent Networks. Proceedings of the 2019 3rd *International Conference on Computer Science & Artificial Intelligence*. https://doi.org/10.1145/3374587.3374622
16) Sami HM. (2021). Portfolio construction using financial ratio indicators and classification through machine learning, *Int. J. Manag. Account,* **3**(4), 83-90. https://doi.org/10.34104/ijma.021.083090
17) Sami HM. (2021). Optimizing organizational overall performance, the use of quantitative choice of HR in carrier quarter enterprise of Bangladesh, *Can. J. Bus. Inf. Stud.,* **3**(3), 49-59. https://doi.org/10.34104/cjbis.021.049059
18) Sami HM, and Arifuzzaman SM. (2021). Comparing pure stock portfolio with stock and crypto-currency mixed portfolio through LSTM to compare & analyze investment opportunities for portfolio performance measurement, *Aust. J. Eng. Innov. Technol*., **3**(3), 45-56. https://doi.org/10.34104/ajeit.021.045056
19) Sami HM, Fardous L, and Ruhit DS. (2021). Portfolio optimization in DSE using finance indicators, LSTM & PyportfolioOpt, *Int. J. Mat. Math. Sci.*, **3**(4), 74-84. https://doi.org/10.34104/ijmms.021.074084
20) Sami HM, Rafatuzzaman M, and Bar A. (2021). Machine learning application for selecting efficient loan applicants in private banks of Bangladesh, *Int. J. Manag. Account*. **3**(5), 114-121. https://doi.org/10.34104/ijma.021.01140121
21) Siami *et al.* (2019). The Performance of LSTM and BiLSTM in Forecasting Time Series. *IEEE Inter Conference on Big Data*, 9-12 Dec. 2019. https://doi.org/10.1109/BigData47090.2019.9005
22) Siami-Namini, S., Tavakoli, N., & Namin, A. S. (2019). The Performance of LSTM and BiLSTM in Forecasting Time Series. 2019 IEEE International Conference on Big Data. https://doi.org/10.1109/bigdata47090.2019.900
23) Wu *et al.* (2018). A New Forecasting Framework for Bitcoin Price with LSTM. *IEEE Inter Conference on Data Mining Workshops*. https://doi.org/10.1109/BigData47090.2019.905
24) Yu, P., & Yan, X. (2019). Stock price prediction based on deep neural networks. *Neural Computing and Applications*. https://doi.org/10.1007/s00521-019-04212-x

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