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Deep Learning Based Financial Forecasting Models

Eray Balat[1], Cem Taylan Ekinci[2], H. Şebnem Arlı[3], Ceren Ulus[4], M. Fatih Akay[5]
[1]*ENKO Technology, Istanbul, Turkey, eray.balat@kolaybi.com, ORCID: 0000-0002-6920-7304*
[2]*ENKO Technology, Istanbul, Turkey, cem.ekinci@kolaybi.com, ORCID: 0000-0001-6067-6246*
[3]*Çukurova University, Adana, Turkey, ssebnemarlii@gmail.com, ORCID: 0000-0001-8236-7487*
[4]*Cukurova University, Adana, Turkey, f.cerenulus@gmail.com, ORCID: 0000-0003-2086-6381*
[5]*Çukurova University, Adana, Turkey, mfakay@cu.edu.tr, ORCID: 0000-0003-0780-0679*

Financial planning involves systematical forecasting and calculation of cash and financial flows into and out of the company. Financial planning is the reconciliation of cash inflows and outflows, both in terms of amount and time by forecasting all types of cash inflows and outflows that will occur during the company's operations. It allows to quickly determine the solution process, make analysis, forecasts and strategic decisions. This study aims to develop financial forecasting models using univariate deep learning methods. For this purpose Long Short Term Memory (LSTM), Bi-directional Long Short Term Memory (Bi-LSTM) and Convolutional Long Short Term Memory (ConvLSTM) have been used. The performance of the developed models has been evaluated using Mean Absolute Percentage Error (MAPE). The dataset includes 464 rows and total inbound and total outbound invoice amount data from June 22nd, 2020 to March 31st, 2022. Forecast models have been developed for 2 different weeks (28.02.2022 – 04.03.2022 and 21.03.2022 – 25.03.2022) and 2 different months (January 2022 and March 2022) randomly selected from the dataset. When the forecast models developed for inbound invoice amount and outbound invoice amount are examined, it is found that satisfactory results have not been obtained for the monthly forecasts. For the weekly forecasts, MAPE's of the forecast models were found to be less than 20% in general.

***Keywords**:* *Deep learning, Financial planning, Financial forecasting.*

1. Introduction

Finance is the process of planning the funds, time, and process that a company needs most beneficially. Financial planning, on the other hand, provides the financing necessary for a business or company for achieving its long and short-term goals. The purpose of financial planning is to create optimal liquidity. Financial planning is the systematic forecasting and calculation of financial flows entering and leaving the company and the determination of future movements. As a management tool, financial planning gives the manager insight into all aspects of the business. It helps to make the right decisions for the allocation of resources to achieve the goals. Financial planning helps the business to adapt more easily to changing economic conditions while managing the business. Companies use financial forecasting to determine how to allocate their resources or what expenses to expect in a given period. Leading companies use new technologies for financial planning and use well-structured planning and forecasting proceses. In this way, companies are able to plan accurately and make effective decisions with more successful forecasts. In general, these tools and applications; can save time, reduce errors, and develop a more disciplined financial management culture that provides the right competitive advantage. It can also strengthen the links between strategic goals and operational and financial plans. In case of a potential problem, strategic decisions can be made by quickly determining the solution process, analysis, and forecasting.

Financial forecasting is a process or operation that forecasts the future performance of a business. Financial forecasting involves forecasting a company's revenues and expenses. In today's challenging global economy, financial forecasts may need to be updated monthly or weekly. Historical performance data is used to create forecasts.

This study aims to develop financial forecasting models using univariate deep learning methods. For this purpose LSTM, Bi-LSTM and ConvLSTM have been used. The performance of the developed models has been evaluated using the MAPE. The dataset includes 464 rows and total inbound and total outbound invoice amount data from June 22nd, 2020 to March 31st, 2022. Forecast models have been developed for 2 different weeks (28.02.2022 – 04.03.2022 and 21.03.2022 – 25.03.2022) and 2 different months (January 2022 and March 2022) randomly selected from the dataset.

In the last few years, various methods have been used for financial forecasting. [1] improved the existing Convolutional Neural Network (CNN) and applied it to financial planning from different perspectives. Firstly, the noise of the collected data set was deleted, and then the clustering result got more stable by Principal Component Analysis (PCA). The empirical results based on specific data from China's stock market showed that the proposed method improved the performance of the forecast. [2] applied Multi-Layer Perceptron (MLP), Autoregressive Integrated Moving Average (ARIMA), Prophet and Long-Short Term Memory (LSTM) for cash flows. [3] demonstrated how machine learning could be used for both forecasting and planning in a simulation study for financial forecasting, planning, and analysis. As the number of data points increased, how forecasting and planning evolves was also explored. [4] proposed to use Support Vector Machine (SVM) to predict the revenue of enterprises. The performance of the models was evaluated using Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and MAPE. [5] utilized three different methods namely Exponential Smoothing, Box-Jenkins, and ANNs for forecasting Turkey’s tourism revenues. The performance of the developed models was evaluated using MAPE. As a result of the analysis performed, it was found that ANN was the best one among the all models applied in this study. [6] proposed Scalable Natural Gradient Boosting Machine, which is simple to implement, readily parallelizable, interpretable, and yields high-quality predictive uncertainty estimates. [7] proposed an approach for revenue forecasting using Light Gradient Boosting Machine (LightGBM). When the results were compared with traditional statistical models such as Logistic Regression (LR), LightGBM showed satisfactory progress in both prediction accuracy and speed. [8] developed a versatile modeling approach that utilized univariate and multivariate models to accurately predict a company's financial performance and identify the best-performing model for capital market management and analysis. [9] investigated financial analysts' income forecasts and a model was developed for income forecast. This study also helped investors and academic researchers understand the determinants of income forecasts. [10] adopted the Monte Carlo simulation to forecast cash flow distribution and the risks caused by uncertainty. This study showed that it is a simple matter to analyze the principal sources of uncertainty in the cash flows and see how much this uncertainty could be reduced by improving the forecasts of sales or costs.

This paper is structured as follows: Section 2 provides information on the methodology. Section 3 presents results and discussion. Section 4 concludes the paper.

2. Methodology

In this study, forecast models were developed with LSTM, Bi-LSTM and ConvLSTM using total data of the daily inbound and outbound invoice amount. While developing the forecast models, using the univariate time series approach, models were trained using only retrospective inbound and outbound invoice amount data. The dataset was in a daily format. Forecast models has been developed for 2 different weeks (28.02.2022 – 04.03.2022 and 21.03.2022 – 25.03.2022) and 2 different months (January 2022 and March 2022) randomly selected from the dataset.

A. LSTM:

LSTM is recursive and is used in deep learning methods. The control flow of LSTM and Recursive Neural Network (RNN) is similar. It transmits information while processing data moving forward. LSTM network has a feedback loop that allows it to analyze entire sequences of data in addition to individual data points. Therefore, these networks are used for classification, processing, and prediction of time series data [11].

B. Bi-LSTM:

Bi-LSTM considers the bidirectional relationship of the input data in the time structure, rather than using only a single input processing direction by the LSTM gate. The current time series data is processed while the upcoming data is considered. Through the gate mechanism, this bidirectional processing increases the information intelligence and adds more structural information. In order to preserve the information properties of the previous and subsequent data and to improve the generalization, Bi-LSTM encodes the information sequentially [12].

C. ConvLSTM:

ConvLSTM network uses the convolutional operation in both input-to-state and state-to-state transitions, eliminating matrix multiplication in LSTM. The current input vectors and past cell states can still be used to derive the temporal information, which means that ConvLSTM network can simultaneously identify the spatial and temporal attributes while also using CNN network to determine the spatial attributes [13].

The hyperparameters of the developed models using inbound invoice amount data are shown in Table 1 through Table 4.

Table 1. *The hyperparameters of the developed models using inbound invoice amount data for 21.03.2022-25.03.2022*

Method	Train Row	Scale Type	Lag Option	Number of Hidden Layers - Neurons	Input - Output Activation Function	Epoch	Batch Size	Learning Rate	Loss Function
LSTM	80%	Standard	Use best N. (N = 9)	1, 256	Tanh, Linear	100	32	$6*10^{-3}$	MAE
Bi-LSTM	80%	Standard	Use all lags. (1 to 7)	1, 200	Tanh, Relu	128	256	$9*10^{-3}$	MSE
ConvLSTM	80%	Standard	Use all lags. (1 to 7)	2, 128, 128	Tanh, Tanh, Linear	100	64	$9*10^{-3}$	MAE

Table 2. *The hyperparameters of the developed models using inbound invoice amount data for 28.02.2022-04.03.2022*

Method	Train Row	Scale Type	Lag Option	Number of Hidden Layers - Neurons	Input - Output Activation Function	Epoch	Batch Size	Learning Rate	Loss Function
LSTM	85%	Standard	Use best N. (N = 3)	3, 512, 450, 300	Linear, Linear, Linear, Linear	150	128	$5*10^{-3}$	MAE
Bi-LSTM	85%	Standard	Use selected. (2, 3, 4, 6, 7)	1, 200	Tanh, Linear	150	32	$7*10^{-3}$	MAE
ConvLSTM	90%	Standard	Use selected. (2, 3, 4)	3, 36, 36, 36	Tanh, Tanh, Tanh, Linear	100	64	$9*10^{-3}$	MAE

Table 3. *The hyperparameters of the developed models using inbound invoice amount data for January 2022*

Method	Train Row	Scale Type	Lag Option	Number of Hidden Layers - Neurons	Input - Output Activation Function	Epoch	Batch Size	Learning Rate	Loss Function
LSTM	80%	Min - Max	Use best N. (N=8)	1, 100	Tanh, Linear	115	256	$4*10^{-3}$	MSE
Bi-LSTM	80%	Standard	Use all lags. (1 to 6)	1, 80	Tanh, Linear	100	256	$4*10^{-3}$	MSE
ConvLSTM	70%	Standard	Use selected. (1, 2, 3, 4, 5, 6)	2, 64, 64	Tanh, Tanh, Linear	128	128	$8*10^{-3}$	MAE

Table 4. *The hyperparameters of the developed models using inbound invoice amount data for March 2022*

Method	Train Row	Scale Type	Lag Option	Number of Hidden Layers - Neurons	Input - Output Activation Function	Epoch	Batch Size	Learning Rate	Loss Function
LSTM	80%	Standard	Use selected. (1, 2, 3, 4, 5)	2, 128, 128	Tanh, Tanh, Linear	256	128	$8*10^{-3}$	MAE
Bi-LSTM	75%	Standard	Use selected. (1, 2, 3, 4, 5)	2, 256, 128	Tanh, Tanh, Linear	256	128	$8*10^{-3}$	MAE
ConvLSTM	85%	Standard	Use all lags. (1 to 18)	1, 150	Sigmoid, Tanh	200	32	$6*10^{-3}$	MAE

The hyperparameters of the developed models using outbound invoice amount data are shown in Table 5 through Table 8.

Table 5. *The hyperparameters of the developed models using outbound invoice amount data for 21.03.2022-25.03.2022*

Method	Train Row	Scale Type	Lag Option	Number of Hidden Layers - Neurons	Input - Output Activation Function	Epoch	Batch Size	Learning Rate	Loss Function
LSTM	80%	Standard	Use selected. (1, 2, 3, 4, 5, 9)	1, 256	Tanh, Linear	100	32	$6*10^{-3}$	MAE
Bi-LSTM	70%	None	Use all lags. (1 to 6)	1, 100	Linear, Linear	100	64	$9*10^{-3}$	MSE
ConvLSTM	75%	None	Use all lags. (1 to 7)	1, 60	Relu, Relu	100	64	$8*10^{-3}$	MSE

Table 6. *The hyperparameters of the developed models using outbound invoice amount data for 28.02.2022-04.03.2022*

Method	Train Row	Scale Type	Lag Option	Number of Hidden Layers - Neurons	Input - Output Activation Function	Epoch	Batch Size	Learning Rate	Loss Function
LSTM	80%	Standard	Use all lags. (1 to 8)	1, 100	Linear, Linear	145	128	$8*10^{-3}$	MSE
Bi-LSTM	75%	Standard	Use all lags. (1 to 6)	2, 100, 90	Linear, Linear, Linear	150	64	$8*10^{-3}$	MSE
ConvLSTM	75%	Standard	Use best N. (N = 12)	1, 80	Linear, Linear	128	128	$9*10^{-3}$	MSE

Table 7. *The hyperparameters of the developed models using outbound invoice amount data for January 2022*

Method	Train Row	Scale Type	Lag Option	Number of Hidden Layers - Neurons	Input - Output Activation Function	Epoch	Batch Size	Learning Rate	Loss Function
LSTM	100%	Min - Max	Use best N. (N=3)	1, 100	Linear, Linear	128	256	$4*10^{-3}$	MAE
Bi-LSTM	75%	Standard	Use selected. (3, 4, 5, 6)	3, 150, 130, 110	Tanh, Tanh, Tanh, Tanh	128	64	$3*10^{-3}$	MSE
ConvLSTM	75%	Standard	Use selected. (1, 2, 3)	1, 150	Linear, Linear	150	128	$9*10^{-3}$	MSE

Table 8. *The hyperparameters of the developed models using outbound invoice amount data for March 2022*

Method	Train Row	Scale Type	Lag Option	Number of Hidden Layers - Neurons	Input - Output Activation Function	Epoch	Batch Size	Learning Rate	Loss Function
LSTM	95%	Standard	Use best N. (N=6)	2, 32, 32	Tanh, Tanh, Linear	256	100	$8*10^{-3}$	MAE
Bi-LSTM	70%	Standard	Use best N. (N=17)	1, 80	Relu, Linear	150	128	$9*10^{-3}$	MSE
ConvLSTM	75%	Standard	Use selected. (1, 4, 5)	3, 50, 40, 30	Sigmoid, Sigmoid, Sigmoid, Sigmoid, Linear	100	64	$9*10^{-3}$	MSE

3. Results and Discussion

MAPE's of the forecast models developed using inbound invoice amount data for the two weeks and two months are shown in Table 9.

Table 9. *MAPE's of the inbound invoice amount models*

Method / Test data period	LSTM	Bi-LSTM	ConvLSTM
21.03.2022-25.03.2022	25.02	18.96	32.4
28.02.2022-04.03.2022	20.6	32.48	29.6
January 2022	48.49	57.52	38.98
March 2022	70.41	99.2	94.31

- For the models developed for 21.03.2022-25.03.2022, Bi-LSTM has the lowest MAPE (18.96%) and ConvLSTM (32.4%) has the highest MAPE.
- For the models developed for 28.02.2022-04.03.2022, LSTM has the lowest MAPE (20.6%) and Bi-LSTM (32.48%) has the highest MAPE.
- For the models developed for January 2022, ConvLSTM has the lowest MAPE (38.98%) and Bi-LSTM (57.52%) has the highest MAPE.
- For the models developed for March 2022, LSTM has the lowest MAPE (70.41%) and Bi-LSTM (99.2%) has the highest MAPE.

It was observed that the value of the standard deviation in March was almost twice as high as the value of the standard deviation in January. In addition, a large number of outliers were found in March. In accordance with these analysis, it was inevitable that models for January would be more successful than the ones for March in monthly forecasts.

MAPE's of the forecast models developed data using outbound invoice amount for the two weeks and two months are shown in Table 10.

Table 10. *MAPE's of the outbound invoice amount models*

Method / Test data period	LSTM	Bi-LSTM	ConvLSTM
21.03.2022-25.03.2022	21.94	15.68	22.30
28.02.2022-04.03.2022	17.20	19.80	20.96
January 2022	64.02	45.69	56.59
March 2022	28.55	29.22	32.25

- For the models developed for 21.03.2022-25.03.2022, Bi-LSTM (15.68%) has the lowest MAPE and ConvLSTM (22.30%) has the highest MAPE.
- For the models developed for 28.02.2022-04.03.2022, LSTM (17.20%) has the lowest MAPE and ConvLSTM (20.96%) has the highest MAPE.
- For the models developed for January 2022, Bi-LSTM (45.69%) has the lowest MAPE and LSTM (64.02%) has the highest MAPE.
- For the models developed for March 2022, LSTM (25.55%) has the lowest MAPE and ConvLSTM (32.25%) has the highest MAPE.

4. Conclusion

In this study, financial forecasting models were developed using inbound-outbound invoice amount data. The forecast models have been developed for two different weeks and two different months using LSTM, Bi-LSTM, and ConvLSTM. The performance of the developed models has been evaluated using MAPE. When the forecast models developed for inbound invoice amount and outbound invoice amount are examined, it is found that satisfactory results have not been obtained for the monthly forecasts. For the weekly forecasts, MAPE's of the forecast models were found to be less than 20% in general.

REFERENCES

[1] W. Dai, "Application of improved convolution neural network in financial forecasting." Journal of Organizational and End User Computing (JOEUC), vol. 34, no. 3, pp. 1-16, 2022.
[2] H. Weytjens, E. Lohmann, M. Kleinsteuber, "Cash flow prediction: MLP and LSTM compared to ARIMA and Prophet." Electronic Commerce Research, vol. 21, no. 2, pp. 371-391, 2021.
[3] H. Wasserbacher, M. Spindler, "Machine learning for financial forecasting, planning and analysis: recent developments and pitfalls", Digital Finance, pp. 1-26, 2021.
[4] H. Lei, H. Cailan, "Comparison of multiple machine learning models based on enterprise revenue forecasting." Asia-Pacific Conference on Communications Technology and Computer Science (ACCTCS), pp. 354-359, January, 2021.
[5] M. Çuhadar, "A comparative study on modelling and forecasting tourism revenues: The case of Turkey." Advances in Hospitality and Tourism Research (AHTR), vol. 8, no. 2, pp. 235-255, 2020.
[6] Z. Zhang, K. Zhao, K. Huang, Q. Jia, Y. Fang, Q. Yu, "Large-scale Uncertainty Estimation and Its Application in Revenue Forecast of SMEs." 2020
[7] C. Xinyue,X. Zhaoyu, Z. Yue, "Using Machine Learning to Forecast Future Earnings." Atlantic Economic Journal, vol. 48, no. 4, pp. 543-545, 2020.
[8] A. Papadimitriou, U. Patel, L. Kim, G. Bang, A. Nematzadeh, X. Liu, "A multi-faceted approach to large scale financial forecasting." In Proceedings of the First ACM International Conference on AI in Finance, pp. 1-8, October, 2020.
[9] T. Lorenz, C. Homburg, "Determinants of analysts' revenue forecast accuracy." Review of Quantitative Finance and Accounting, vol. 51, no. 2, pp. 389-431, 2018.
[10] I. Leifer, L. Leifer,2016, "Small business valuation with use of cash flow stochastic modeling." In 2016 Second International Symposium on Stochastic Models in Reliability Engineering, Life Science and Operations Management (SMRLO), pp. 511-516, February, 2016.
[11] A. Manowska, "Using the LSTM Network to Forecast the Demand for Electricity in Poland." Applied Sciences, vol. 10, no. 23, pp. 8455, 2020.
[12] B. Liu, C. Song, Q. Wang, Y. Wang, "Forecasting of China's solar PV industry installed capacity and analyzing of employment effect: based on GRA-Bi-LSTM model." Environmental Science and Pollution Research, vol. 29, no. 3, pp. 4557-4573, 2022.
[13] S. Siami-Namini, N. Tavakoli, A. S. Namin, "A comparison of ARIMA and LSTM in forecasting time series." In 2018 17th IEEE international conference on machine learning and applications (ICMLA), pp. 1394-1401, December, 2018.