3. Metode *Kernel Principal Component Analysis-Long Short Term Memory* dengan fungsi kernel POLY, 5 *timesteps* dan 50 *unit* LSTM menjadi model terbaik untuk prediksi harga saham BBRI pada hari bursa selanjutnya, dengan membandingkan pada data *testing* harga saham sebenarnya dan hasil prediksinya menghasilkan RMSE sebesar 145.7041, MAE sebesar 100.4997, dan MAPE sebesar 2.7620%. Hasil prediksi lengkap terlampir pada lampiran 12.

5.2. Saran

Berdasarkan penelitian yang telah dilakukan, terdapat beberapa saran yang dapat diberikan, diantarnya adalah sebagai berikut.

1. Untuk mendapatkan hasil reduksi variabel metode *Kernel Principal Component Analysis* yang lebih baik, pada penelitian selanjutnya disarankan untuk melakukan *hyperparameter tuning* pada masing-masing kernel yang dipilih.
2. Penelitian selanjutnya dapat membandingkan dengan metode reduksi dimensi nonlinier yang lain, maupun metode reduksi dimensi yang memanfaatkan jaringan saraf tiruan.
3. Kasus prediksi harga saham menggunakan data hasil reduksi dimensi pada penelitian selanjutnya disarankan untuk membandingkan model varian lain dari LSTM dan RNN standar, seperti Bi-LSTM, Stacked-LSTM, Bi-RNN, Stacked-RNN dan pengembangan lainnya.
4. Untuk mengetahui lebih jelas bagaimana arsitektur model dapat mengatasi masalah *vanishing gradient* ataupun dampak masalah tersebut, disarankan untuk menggunakan *timesteps* yang lebih panjang lagi.

DAFTAR PUSAKA

Aizerman, M., Braveman, E., & Rozonoer, L. (1964). Theoretical foundations of the potential function method in pattern recognition learning. *Automation and Remote Control*, *25*, 821-837.

Anton, H., & Rorres, C. (2000). *Elementary Linear Algebra.* United States of America: John Wiley & Sons, Inc.

Atsalakis, G. S., & Valavanis, K. P. (2009). Surveying stock market forecasting techniques – Part II: Soft computing methods. *Expert Systems with Applications*, *36*(3), 5932-5941.

Bengio, Y., Simard, P., & Frasconi, P. (1994). Learning long-term dependencies with gradient descent is difficult. *IEEE Transactions on Neural Network*, *5*, 157-166.

Boser, B. E., Guyon, I. M., & Vapnik, V. N. (1992). A training algorithm for optimal margin classifiers. *In D. Haussler, Proceedings of the 5th Annual ACM Workshop on Computational Learning Theory* (pp. 144-152). Pittsburgh: ACM Press.

Brownlee, J. (2017). *Long Short-Term Memory Networks With Python.* Melbourne: Machine Learning Mastery.

Courant, R., & Hilbert, D. (1953). *Methods of mathematical physics (Vol. 1).* New York: Interscience.

Deboeck, G. J. (1994). *Trading on the edge: Neural, genetic, and fuzzy sistems for chaotic financial markets.* New York: Wiley.

Duchi, J., Hazan, E., & Singer, Y. (2011). Adaptive Subgradient Methods for Online Learning and Stochastic Optimization. *Journal of Machine Learning Research*, 2121-2159.

Faurina, R. (2019). *Klasifikasi Pergerakan Harga Saham Jangka Pendek Menggunakan Principal Component Analysis dan Jaringan Long Short Term Memory : Studi Kasus Pada Saham Bursa Efek Indonesia.* Tesis, Departemen Teknik Elektro dan Teknologi Informasi Fakultas Teknik UGM, Yogyakarta.

Fausett, L. (1994). *Fundamental of Neural Network.* USA: Prentice-Hall Inc.

Goodfellow, I., Bengio, Y., & Courville, A. (2016). *Deep Learning.* Cambridge: MIT Press.

Gunduz, H. (2021). An efcient stock market prediction model using hybrid feature reduction method based on variational autoencoders and recursive feature elimination. *Financial Innovation, 7*(28).

Gunduz, H., Yaslan, Y., & Cataltepe, Z. (2017). Stock daily return prediction using expanded features and feature selection. *Turkish Journal ofElectrical Engineering and Computer Sciences, 25*(6), 4829-4840.

Hilbert, D. (1904). Grundz ̈uge einer allgemeinen Theorie der linearen Integralgleichungen. *Nachrichten der G ̈ottinger Akademie der Wissenschaften, Mathematisch-Physikalische Klasse*, 49-91.

Hochreiter, S., & Schmidhuber, J. (1997). Long Short-Term Memory. *Neural Computation*, 1735–1780.

Kingma, D. P., & Ba, J. L. (2015). ADAM: A METHOD FOR STOCHASTIC OPTIMIZATION. *The 3rd International Conference for Learning Representations.*

Mulyaningtyas, E. D. (2021). *Metode Principal Component Analysis-Back Propagation Artificial Neural Network (PCA-BP ANN) Untuk Prediksi Harga Saham PT. Bank Rakyat Indonesia.* Skripsi, Departemen Matematika FMIPA UGM, Yogyakarta.

Naik, N., & Mohan, B. R. (2019). Optimal Feature Selection of Technical Indicator and Stock Prediction using Machine Learning Technique. *Emerging Technologies in Computer Engineering: Microservices in Big Data Analytics*, 261-268.

Rumelhart, D., Hinton, G., & Williams, R. (1986). Learning representations by back-propagating errors. *Nature, 323*, 533-536.

Schölkopf, B., Smola, A., & Müller, K.-R. (1998). Nonlinear Component Analysis as a Kernel Eigenvalue Problem. *Neural Computation, 10*(5), 1299–1319.

Sethia, A., & Raut, P. (2019). Application of LSTM, GRU & ICA for Stock Price. *Information and Communication Technology for Intelligent Systems*, 479-487.

Tielman, T., & Hinton, G. (2012). *Lecture 6.5-rmsprop: Divide the Gradient by a Running Average of Its Recent Magnitude.* COURSERA: Neural Networks for Machine Learning.

Vapnik, V. (1995). *The nature of statistical learning theory*. New York: Springer-Verlag.

Wei, W. W. (2006). *Time Series Analysis Univariate and Multivariate Methods.* Boston: Pearson Education.

Wen, F., Xu, L., Ouyang, G., & Gang, K. (2019). Retail investor attention and stock price crash risk: evidence from china. *International Review of FInancial Analysis*, 376.

Wen, Y., Lin, P., & Nie, X. (2020). Research of Stock Price Prediction Based on PCA-LSTM . *IOP Conf. Series: Materials Science and Engineering*.

Yaser, S., & Atiya, A. F. (1996). Introduction to financial forecasting. *Applied Intelligence, 6(3)*, 205-213.

Zhong, X., & Enke, D. (2017). Forecasting daily stock market return using dimensionality reduction. *Expert Systems With Applications*, *67*, 126-139.