ILKOM Jurnal Ilmiah Vol. 16, No. 2, August 2024, pp. 210-220
Accredited 2nd by RISTEKBRIN No. 200/M/KPT/2020; E-ISSN 2548-7779 | P-ISSN 2087-1716

Research Article

Enhanced Multivariate Time Series Analysis Using LSTM: A Comparative Study of Min-Max and Z-Score Normalization Techniques

Andri Pranolo [a,1,*]; Faradini Usha Setyaputri [b,2]; Andien Khansa'a Iffat Paramarta [b,3]; Alfiansyah Putra Pertama Triono [b,4]; Akhmad Fanny Fadhilla [b,5]; Ade Kurnia Ganesh Akbari [b,6]; Agung Bella Putra Utama [b,7]; Aji Prasetya Wibawa [b,8]; Wako Uriu [c,9]
[a] *Universitas Ahmad Dahlan, Jl. Ringroad Selatan 598M+P77, Yogyakarta 55191, Indonesia*
[b] *Universitas Negeri Malang, Jl. Semarang no. 5, Malang 65145, Indonesia*
[c] *Chikushi Jogakuen University, 2-chōme-12-1 Ishizaka, Fukuoka 818-0118, Japan*
[1] *andri.pranolo@tif.uad.ac.id;* [2] *faradini.usha@gmail.com;* [3] *khansaandien@gmail.com;* [4] *alfiansyah.putrapt.1905356@student.um.ac.id;* [5] *4akhmadfadhil512@gmail.com;* [6] *ade.kurniaganesh.1905356@students.um.ac.id;* [7] *agungbpu02@gmail.com;* [8] *aji.prasetya.ft@um.ac.id;* [9] *ue2017119@chikushi-u.ac.jp*
* *Corresponding author*

Article history: Received September 03, 2024; Revised September 15, 2024; Accepted September 28, 2024; Available October 20, 2024,

Abstract

The primary objective of this study is to analyze multivariate time series data by employing the Long Short-Term Memory (LSTM) model. Deep learning models often face issues when dealing with multivariate time series data, which is defined by several variables that have diverse value ranges. These challenges arise owing to the potential biases present in the data. In order to tackle this issue, it is crucial to employ normalization techniques such as min-max and z-score to guarantee that the qualities are standardized and can be compared effectively. This study assesses the effectiveness of the LSTM model by applying two normalizing techniques in five distinct attribute selection scenarios. The aim of this study is to ascertain the normalization strategy that produces the most precise outcomes when employed in the LSTM model for the analysis of multivariate time series. The evaluation measures employed in this study comprise Mean Absolute Percentage Error (MAPE), Root Mean Square Error (RMSE), and R-Squared (R2). The results suggest that the min-max normalization method regularly yields superior outcomes in comparison to the z-score method. Min-max normalization specifically resulted in a decreased MAPE and RMSE, as well as an increased R2 value. These improvements indicate enhanced accuracy and performance of the model. This paper makes a significant contribution by doing a thorough comparison analysis of normalizing procedures. It offers vital insights for researchers and practitioners in choosing suitable preprocessing strategies to improve the performance of deep learning models. The study's findings underscore the importance of selecting the appropriate normalization strategy to enhance the precision and dependability of multivariate time series predictions using LSTM models. To summarize, the results indicate that min-max normalization is superior to z-score normalization for this particular use case. This provides a useful suggestion for further studies and practical applications in the field. This study emphasizes the significance of normalization in analyzing multivariate time series and contributes to the larger comprehension of data preprocessing in deep learning models.

Keywords: LSTM; Min-Max; Multivariate Time Series; Normalization; Z-Score.

Introduction

Multivariate time series analysis is a statistical technique used to examine data collected at different time points [1]. Time series can be classified into two categories: univariate, which involves measurements based on a single property, and multivariate, which consists of a sequence of measurements based on multiple connected qualities [2]. Multivariate time series analysis is extensively employed in diverse domains, including healthcare [3], economics [4], and other sciences [5]. Nevertheless, the analysis of multivariate time series data is intricate because of the interaction among the features.

Deep learning has emerged as a viable method for tackling the intricacies of analyzing multivariate time series data. Deep learning is a machine learning subfield that uses neural networks with multiple layers and parameters to explore and understand intricate data [6]. Several advanced deep-learning models have been created to analyze time series data. These models include Recurrent Neural Networks (RNN) [7], Convolutional Neural Networks (CNN) [8], LSTM [9], Gated Recurrent Units (GRU) [10], and Bidirectional LSTM (Bi-LSTM) [11].

http://dx.doi.org/10.33096/ilkom.v16i2.2333.210-220

Although these models have succeeded, they each have their constraints. For example, Recurrent Neural Networks (RNNs) frequently encounter the vanishing gradient problem issue, making it challenging to train long-term dependencies [12] effectively. CNNs, although proficient in capturing localized patterns, may experience difficulties handling the inherent temporal dependencies present in time series data. LSTM and GRU models, despite being specifically developed to tackle the problem of vanishing gradients, can be computationally demanding and necessitate significant fine-tuning to attain optimal performance [13]. Bi-LSTM models increase complexity and computational expense because they are bidirectional.

The broad spectrum of attribute values is an obstacle in analyzing multivariate time series data. Deep learning models may exhibit bias and receive poor performance when presented with varying value ranges [14]. Thus, normalization is essential to standardize the value ranges of these characteristics. Normalization in the context of multivariate time series analysis involves transforming the value ranges of characteristics into uniform intervals. This allows deep learning models to treat these qualities proportionally [15]. Multiple normalizing techniques exist, such as min-max normalization and z-score normalization. Choosing the correct normalization technique is vital for the deep learning model to achieve the best outcomes in data analysis.

Nevertheless, previous studies have predominantly concentrated on the utilization of normalization techniques for univariate time series or broader machine learning endeavors [16]–[20], leaving little room for investigating their precise effects on multivariate time series data within deep learning frameworks. In addition, although min-max and z-score normalization strategies are commonly employed, a dearth of comprehensive comparison studies precisely assess their effectiveness in the context of multivariate time series data employing LSTM models.

This study aims to assess the effectiveness of the LSTM model in evaluating multivariate time series data by utilizing various normalizing techniques. The main goal is to ascertain the optimal normalization technique, either min-max or z-score, to boost the performance of the LSTM model. This study aims to evaluate the precision of the model by utilizing measures such as MAPE, RMSE, and R2. The uniqueness of this research resides in its comparative examination of normalization strategies, specifically in the setting of multivariate time series data using the LSTM model. It offers valuable insights into which normalization method produces superior performance and accuracy.

This paper enhances the field of multivariate time series analysis and deep learning by:
1. Conducting a comprehensive comparison investigation of the min-max and z-score normalization techniques when applied to the LSTM model.
2. This study aims to illustrate the influence of various normalization strategies on the performance and accuracy of the LSTM model while dealing with multivariate time series data.
3. This paper provides practical insights and advice for researchers and practitioners regarding selecting suitable normalization approaches to enhance the performance of deep learning models in analyzing time series data.
4. This study aims to improve the understanding of how normalization impacts the performance of LSTM models, making a valuable contribution to data preprocessing and model optimization in deep learning.

The organization of this article is structured as follows: Section 2 provides a comprehensive description of the technique used in this research. It includes information on the data collection procedure, the preprocessing processes used, the normalization methods applied, and the development of the LSTM model. Section 3 analyzes the data, explaining how the LSTM model performed when alternative normalizing strategies were used. Section 4 summarizes the main discoveries and offers suggestions for future study paths.

Method

This study utilizes the Cross-Industry Standard Process for Data Mining (CRISP-DM) approach, a widely acknowledged standard for data mining projects in many sectors [21]. The CRISP-DM framework consists of six steps (**Figure 1**): Business Understanding, Data Understanding, Data Preparation, Modeling, Evaluation, and Deployment [22]. Providing a methodical and comprehensive approach to the investigation is essential at every stage.

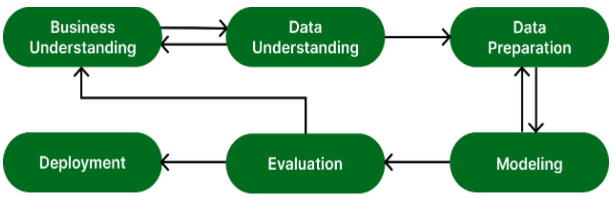

Figure 1. CRISP-DM research flow.

A. Business Understanding

The main objective of conducting Business Understanding is to understand the research's aim [23] comprehensively. When examining multivariate time series using deep learning models, it is crucial to consider the state of the data being utilized [24]. The main objective of this research is to assess the efficacy of various normalization techniques, specifically min-max, and z-score, in enhancing the performance of the LSTM model for analyzing multivariate time series data. This requires comprehending the influence of different normalizing procedures on the accuracy and resilience of the model. It is crucial to address the diverse ranges of attribute values in multivariate time series data to improve the predictive capabilities of a model.

In multivariate time series data, attributes often have different value ranges, leading to potential biases in model training [25]. Normalization methods mitigate these biases by scaling the attributes to comparable ranges. The study aims to determine which normalization technique, min-max or z-score, provides better results regarding MAPE, RMSE, and R2 metrics. This understanding will guide the selection of appropriate preprocessing methods for enhancing deep learning model performance in real-world applications.

B. Data Understanding

The dataset utilized in this study is obtained from Kaggle, specifically named "Hourly Energy Demand Time Series Forecast," including the timeframe from January 2015 to December 2018. The dataset consists of 35,064 instances and 28 attributes, all of which are of the float data type. The desired attribute is "Total load actual." The dataset includes a variety of attributes, such as different types of energy generation (biomass, fossil fuels, hydro, solar, etc.), energy forecasts, and actual loads. A thorough understanding of the dataset is crucial for effective preprocessing and model training. Details of each attribute are in **Table 1**.

Table 1. Dataset Attribute Details

No	Attributes	Description (min, max)	Correlation
1	Generation of biomass	(0, 592)	0.08329
2	Generation of fossil brown coal/lignite	(0, 999)	0.28046
3	Generation of fossil coal/derived gas	(0)	NaN
4	Generation of fossil gas	(0, 20034)	0.54891
5	Generation of fossil hard coal	(0, 8359)	0.39656
6	Generation of fossil oil	(0, 449)	0.49709
7	Generation of fossil oil shale	(0)	NaN
8	Generation of fossil peat	(0)	NaN
9	Geothermal generation	(0)	NaN
10	Generation hydro-pumped storage aggregated	NaN	NaN
11	Generation hydro-pumped storage consumption	(0, 4523)	-0.56281
12	Generation hydro run-off river and poundage	(0, 2000)	0.11857
13	Generation of hydro water reservoir	(0, 9728)	0.47948
14	Generation marine	(0)	NaN
15	Generation nuclear	(0, 7117)	0.08566
16	Generation other	(0, 106)	0.10069
17	Generation of other renewables	(0, 119)	0.18171
18	Generation solar	(0, 5792)	0.39619
19	Generation waste	(0, 357)	0.07731
20	Offshore wind generation	(0)	NaN
21	Onshore wind generation	(0, 17436)	0.04008
22	Forecast solar day ahead	(0, 5836)	0.40436
23	Forecast wind offshore day ahead	NaN	NaN
24	Forecast wind onshore day ahead	(247, 17430)	0.03760
25	Total load forecast	(18105, 41390)	0.99513
26	Total load actual	(18041, 41015)	1.0000

No	Attributes	Description (min, max)	Correlation
27	Price day ahead	(2.06, 98.69)	0.47389
28	Actual price	(9.33, 99.95)	0.43613

Initial data exploration involves identifying missing values, understanding the distribution of each attribute, and examining the relationships between attributes. This step ensures that the dataset is suitable for analysis and helps design appropriate preprocessing strategies. By gaining insights into the data, researchers can make informed decisions about handling missing values, selecting relevant attributes, and applying suitable normalization techniques.

C. Data Preparation

Data preparation is an essential stage in our study, encompassing various critical procedures to guarantee that the dataset is prepared for analysis and model training [26]. One of the initial tasks in data preparation involves addressing missing values, which are frequently encountered in extensive datasets and can substantially impact the performance of models [27]. This study addresses missing data with the deletion approach, which removes rows or columns containing missing values [28]. Two parameters, namely Generation hydro pumped storage aggregated and Forecast wind offshore day ahead, are removed from the analysis because of significant missing data. This decreases the number of attributes from 28 to 26, guaranteeing a more dependable dataset for following procedures.

Normalization is a crucial step in data preparation that focuses on normalizing the value ranges of attributes. This study applies two normalizing techniques: min-max normalization and z-score normalization. Min-max normalization is a data scaling technique that transforms the data to a specific range, usually between 0 and 1 [29]. This is achieved by applying the method mentioned in (1). This approach guarantees that all attribute values are confined to a consistent range, enabling equitable comparison and analysis [30]. Alternatively, z-score normalization adjusts the data with an average value of 0 and a standard deviation of 1 [31]. This is achieved by applying the procedure mentioned in (2). This method aids in aligning the data and standardizing the distribution, rendering it appropriate for models sensitive to the magnitude of input features. **Table 2** displays the outcomes of applying min-max and z-score normalization techniques to the property called Total load actual.

$$x' = \frac{(x - x_{min})}{(x_{max} - x_{min})} \tag{1}$$

$$x' = \frac{x - \mu}{\sigma} \tag{2}$$

Table 2. Normalization Results

Actual Value	Min-max Normalization Value	Z-score Normalization Value
25385	0.319666	-0.723934
24382	0.276008	-0.943172
...	...	...
29735	0.509010	0.226902
28071	0.436580	-0.136820

Once the data has been normalized, attribute selection is carried out to choose the most pertinent characteristics for the LSTM model. The study evaluates five different attribute selection scenarios to identify the most effective attribute set: utilizing all attributes, excluding attributes with NaN or negative correlations, selecting the top 5 attributes based on correlation with the target, selecting the top 3 attributes based on correlation with the target, and utilizing only the target attribute. Correlation analysis evaluates the connection between the target attribute and other aspects, guiding the selecting attributes. Reducing the dimensionality of the data is crucial to enhancing the efficiency and effectiveness of the model by prioritizing the most influential attributes.

D. Modeling

The modeling phase entails constructing and refining the LSTM model to evaluate multivariate time series data. The LSTM model is chosen due to its capacity to manage sequential data with extended-term relationships, rendering it appropriate for time series analysis. The LSTM model's design comprises multiple hyperparameters that must be tuned to attain optimal performance [32].

Hyperparameter tuning is performed by the grid search technique, which methodically investigates all potential combinations of provided hyperparameters to identify the optimal set [33]. The hyperparameters examined in this study encompass batch size, epoch count, hidden layer count, neuron count, loss function, and optimizer [34]. The grid search examines the values listed in **Table 3** [35].

Table 3. Grid Search Hyperparameter Tuning

Parameters	Search Space	Results
Batch Size	'100', '1000'	100
Epoch	'50', '100'	50
Hidden Layer	'2', '5', '10'	2
Loss Function	'MSE', 'MAE', 'huberloss'	MSE
Neuron	'32', '64'	32
Optimizer	'Adam', 'Rmsprop'	Rmsprop

The LSTM model is trained and evaluated using a data split ratio of 70:30. Consequently, 70% of the data is allocated for training the model, while the remaining 30% is reserved for evaluating its performance. The training entails inputting the normalized and preprocessed data into the LSTM model and iteratively changing the weights and biases via backpropagation to minimize the loss function.

After training the model, its performance is assessed using the testing dataset. The model's performance is evaluated using assessment measures such as MAPE, RMSE, and R2. MAPE quantifies the precision of the model's forecasts, RMSE denotes the magnitude of the model's prediction discrepancy, and R2 gauges the extent to which the independent variables can account for the variability in the dependent variable.

The study attempts to discover the most effective normalization strategy, either min-max or z-score, in improving the performance of the LSTM model through the modeling process. An analysis of several attribute selection situations and hyperparameter combinations is conducted to determine the ideal configuration for precise and resilient time-series predictions. This stage converts the prepared data into practical insights and verifies the model's ability to make accurate predictions.

E. Evaluation

The assessment phase entails analyzing the performance of the LSTM model by utilizing the testing dataset to ascertain the efficacy of the normalization procedures, namely min-max, and z-score. The evaluation centers around three primary metrics: MAPE, RMSE, and R2 [36]. The MAPE quantifies the precision of the model's forecasts by representing the prediction discrepancies as a % of the actual values. This metric demonstrates the model's performance over various data ranges, as shown in (3). RMSE, however, measures the model's prediction error by using the square root of the average of the squared differences between the predicted and actual values. This makes it more responsive to significant mistakes, as shown in (4). Finally, R2 calculates the amount of variance in the dependent variable that can be predicted by the independent variables, providing information about the model's ability to explain the data, as shown in (5).

$$MAPE = \frac{100\%}{N}\sum_{i=1}^{N}\left|\frac{y_i - \hat{y}_i}{y_i}\right| \tag{3}$$

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y}_i)^2} \tag{4}$$

$$R2 = \frac{\sum_{i=1}^{N}(y_i - \bar{y})(\hat{y}_i - \bar{\hat{y}})}{\sqrt{\sum_{i=1}^{N}(y_i - \bar{y})^2}\ \sqrt{\sum_{i=1}^{N}(\hat{y}_i - \bar{\hat{y}})^2}} \tag{5}$$

The LSTM model's performance is compared using min-max and z-score normalization across five attribute selection scenarios. These scenarios include using all attributes, excluding attributes with NaN or negative correlations, selecting the top 5 attributes based on correlation with the target, selecting the top 3 attributes based on correlation with the target, and using only the target attribute. The study seeks to determine the best mix of features and normalization approach that produces the most precise and dependable predictions by analyzing various scenarios. The findings are displayed in comprehensive tables and graphs, emphasizing the disparities in model efficacy across each situation. This thorough assessment offers valuable insights into the influence of normalization techniques on the LSTM model's capacity to handle multivariate time series data. It guides future research and practical applications in selecting the most efficient preprocessing strategies for time series analysis.

F. Deployment

In the last stage, the results are reported, and the performance of the LSTM model is compared using the min-max and z-score normalization methods. The results are displayed using graphs and tables to demonstrate the efficacy of each normalizing procedure.

Furthermore, the paper offers practical suggestions derived from the findings, assisting researchers and practitioners in choosing the suitable normalization technique for their particular applications. This deployment phase aims to successfully communicate and use the insights gained from the research in real-world circumstances to improve the performance of LSTM models in multivariate time series analysis.

The method section offers a thorough and organized way to assess normalization procedures' influence on the effectiveness of LSTM models in analyzing multivariate time series.

Results and Discussion

This section provides the findings of the comparison analysis conducted on the Min-Max and Z-Score normalization strategies when applied to the LSTM model for multivariate time series data. The evaluation criteria consist of MAPE, RMSE (Root Mean Square Error), and R2 (Coefficient of Determination). The evaluation is performed in five distinct attribute selection scenarios: utilizing all attributes, excluding attributes with NaN or negative correlations, selecting the top 5 attributes based on correlation with the target, selecting the top 3 attributes based on correlation with the target, and utilizing only the target attribute. The findings are depicted using bar charts for each performance parameter. The evaluation value is derived by calculating the mean values of MAPE, RMSE, and R2 from 5 trials. **Figures 2** to **4** display the MAPE, RMSE, and R2 values for both normalizing strategies in various settings.

Figure 2 demonstrates that the Min-Max normalization consistently yields lower MAPE values than Z-Score normalization in all cases. The Min-Max normalization method obtains the lowest MAPE of 3.877% in the scenarios when all attributes and the top 5 attributes are considered. In contrast, Z-Score normalization yields larger MAPE values, with the most outstanding value being 9.1743% in the scenario, including the top 3 qualities.

As illustrated in **Figure 3**, the RMSE values are significantly lower for Min-Max normalization compared to Z-Score normalization. The best RMSE achieved with Min-Max normalization is 0.0624, observed in the scenarios with all attributes and without NaN or negative attributes. Z-Score normalization, however, results in much higher RMSE values, with the highest being 0.7660 in the top 3 attributes scenario.

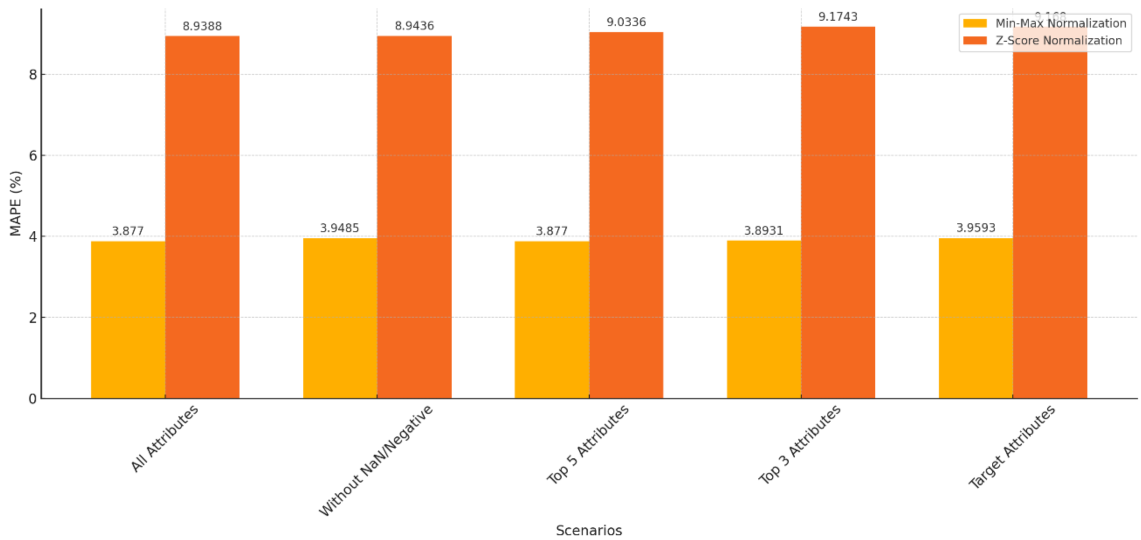

Figure 2. Comparison of MAPE by Different Normalization Techniques Across Scenarios.

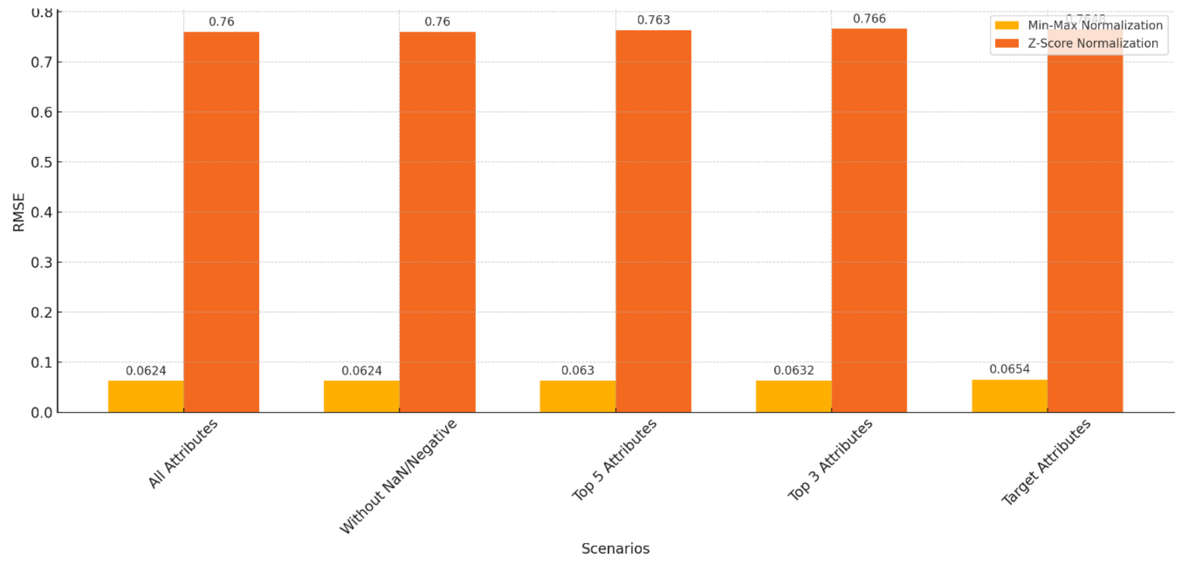

Figure 3. Comparison of RMSE by Different Normalization Techniques Across Scenarios.

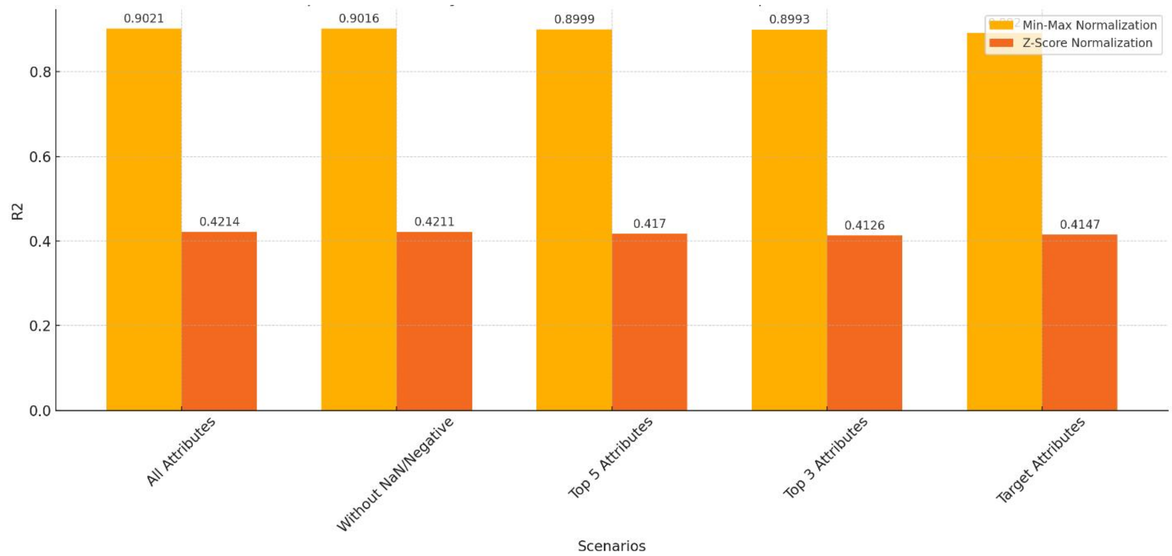

Figure 4. Comparison of R2 by Different Normalization Techniques Across Scenarios.

The R2 values indicate that Min-Max normalization leads to higher R2 values, indicating better model performance and a higher proportion of variance explained by the model from **Figure 4**. The highest R2 value for Min-Max normalization is 0.9021 in the scenario with all attributes. Z-Score normalization consistently shows lower R2 values, with the lowest being 0.4126 in the top 3 attributes scenario.

The comparative analysis demonstrates that Min-Max normalization outperforms Z-Score normalization in MAPE, RMSE, and R2 across all tested scenarios. Specifically, Min-Max normalization results in lower errors (MAPE and RMSE) and higher R2 values, which indicate a more accurate and reliable model performance. The higher efficacy of Min-Max normalization can be ascribed to its capacity to rescale data within a predetermined range, hence permitting enhanced learning and generalization by the LSTM model. This is particularly crucial for time series data with varying ranges of attributes, as Min-Max normalization ensures that all attributes are treated proportionally.

These findings are consistent with prior research. An example is a study on predicting water levels in waterfalls in Malaysia, which demonstrated that models using Min-Max normalization yielded superior RMSE compared to those using Z-Score normalization [37]. Another study revealed that Min-Max normalization provided lower error values than Z-Score normalization in predicting the Nepal stock exchange [38]. However, there are studies with results that differ from these findings.

An investigation on forecasting characteristics of Coal Fired Power Plants (PLTU) found that models utilizing Z-Score normalization yielded a lower MAPE compared to models using Min-Max normalization [39]. The divergent outcomes may be attributed to the distinct attributes of the examined data. The accuracy of forecasts in practical applications, such as energy demand forecasting or healthcare monitoring, can be considerably influenced by the choice of normalization technique. The findings of this work offer valuable insights for researchers and practitioners in choosing the suitable normalization technique to improve the efficiency of deep learning models in time series analysis.

The findings have wide-ranging implications for the more significant Sustainable Development Goals (SDGs) framework, including Goal 7: Affordable and Clean Energy. Objective 13: Taking action to address climate change. Precise energy demand forecasting can facilitate the incorporation of renewable energy sources, improve grid stability, and decrease greenhouse gas emissions by optimizing energy generation and consumption. This study aims to enhance sustainable energy practices and reduce the effects of climate change by improving the precision of time series predictions by implementing efficient normalization procedures. In the healthcare industry, where complicated multivariate time series data is frequently encountered (such as patient monitoring systems), a suitable normalizing technique can enhance predictive models for patient outcomes, resulting in improved healthcare delivery and patient management.

This aligns with Sustainable Development Goal 3: Good Health and Well-being, as it aims to guarantee healthy lifestyles and enhance well-being for people of all ages. This research has significant implications for economic forecasting, as it can provide precise predictions that can be used to make well-informed policy decisions, mitigate risks, and improve financial stability. This is in alignment with the Sustainable Development Goals (SDGs). Goal 8 aims to achieve sustained, inclusive, and sustainable economic growth and promote full and productive employment and decent work opportunities. To summarize, this study emphasizes the significance of choosing suitable normalization strategies to improve the efficiency of LSTM models in analyzing multivariate time series.

The results offer practical suggestions for researchers and professionals and emphasize the broader influence of precise time series forecasts on attaining sustainable development objectives and enhancing practical applications in different industries. Subsequent investigations could delve into integrating additional sophisticated normalizing techniques and their impact on other categories of deep learning models, aiming to improve the precision and practicality of time series predictions. Conducting tests on different datasets with different characteristics might assist in confirming the applicability of these findings. Furthermore, investigating alternative normalization techniques and assessing their influence on various deep-learning models could yield a more thorough comprehension of the preprocessing effects.

Conclusion

This study examines the efficacy of min-max and z-score normalization strategies in improving the performance of the LSTM model for analyzing multivariate time series. The results indicate that min-max normalization consistently performs better than z-score normalization in different attribute selection circumstances. Min-max normalization specifically resulted in lower MAPE, RMSE, and better coefficient of determination (R2), indicating an improved level of accuracy and predictive ability for the model. The main contribution of this research is its thorough comparative investigation of normalizing strategies implemented on the LSTM model. The work offers valuable insights for researchers and practitioners in choosing suitable preprocessing techniques to enhance the performance of deep learning models in time series analysis. Moreover, the results emphasize the broader influence of precise time series forecasts in attaining Sustainable Development Goals (SDGs), including enhancing energy management, healthcare provision, and economic projection.

Although the results of this study show promise, some limitations need to be considered. Initially, the analysis relies on a solitary dataset, potentially constraining the conclusions' applicability. Results may vary depending on the properties of different datasets. Furthermore, the study exclusively examines implementing two normalization strategies: min-max and z-score. Additional normalizing and preprocessing techniques may be investigated to improve model performance further. Finally, although the hyperparameter tuning procedure is thorough, it might still be improved by employing more sophisticated optimization techniques to guarantee the optimal model configuration. Future research should aim to test the proposed normalizing techniques in a broader range of datasets with various characteristics, thus addressing the constraints mentioned to validate the findings.

Furthermore, investigating alternative normalization techniques and assessing their influence on various deep-learning models could yield a more thorough comprehension of the preprocessing effects. Advanced techniques for optimizing hyperparameters, such as Bayesian optimization or evolutionary algorithms, can be used to improve the model's performance further. Furthermore, exploring the incorporation of normalization techniques into other data pretreatment procedures, such as feature engineering and dimensionality reduction, may result in more resilient and precise models for analyzing multivariate time series. To summarize, this research highlights the significance of choosing suitable normalization strategies to improve the performance of LSTM models in multivariate time series analysis. The results offer practical suggestions for enhancing the precision of the model and highlight the substantial practical consequences of precise predictions of time series in different industries, thereby contributing to the overarching objective of sustainable development.

References

[1] Y. Zou, R. V. Donner, N. Marwan, J. F. Donges, and J. Kurths, "Complex network approaches to nonlinear time series analysis," *Phys. Rep.*, vol. 787, pp. 1–97, Jan. 2019, doi: 10.1016/j.physrep.2018.10.005.

[2] F. Karim, S. Majumdar, H. Darabi, and S. Harford, "Multivariate LSTM-FCNs for time series classification," *Neural Networks*, vol. 116, pp. 237–245, Aug. 2019, doi: 10.1016/j.neunet.2019.04.014.

[3] C. Qin, M. Liu, X. Guo, and J. Liu, "Human Resources in Primary Healthcare Institutions before and after the New Healthcare Reform in China from 2003 to 2019: An Interrupted Time Series Analysis," *Int. J. Environ. Res. Public Health*, vol. 19, no. 10, 2022, doi: 10.3390/ijerph19106042.

[4] H. Apaydin, H. Feizi, M. T. Sattari, M. S. Colak, S. Shamshirband, and K. W. Chau, "Comparative analysis of recurrent neural network architectures for reservoir inflow forecasting," *Water (Switzerland)*, vol. 12, no. 5, pp. 1–18, 2020, doi: 10.3390/w12051500.

[5] A. B. P. Utama, A. P. Wibawa, Muladi, and A. Nafalski, "PSO based Hyperparameter tuning of CNN Multivariate Time-Series Analysis," *J. Online Inform.*, vol. 7, no. 2, pp. 193–202, 2022, doi: 10.15575/join.v7i2.858.

[6] J. Runge and R. Zmeureanu, "Forecasting Energy Use in Buildings Using Artificial Neural Networks: A Review," *Energies*, vol. 12, no. 17, p. 3254, Aug. 2019, doi: 10.3390/en12173254.

[7] H. Hewamalage, C. Bergmeir, and K. Bandara, "Recurrent Neural Networks for Time Series Forecasting: Current status and future directions," *Int. J. Forecast.*, vol. 37, no. 1, pp. 388–427, Jan. 2021, doi: 10.1016/j.ijforecast.2020.06.008.

[8] I. Koprinska, D. Wu, and Z. Wang, "Convolutional Neural Networks for Energy Time Series Forecasting," in *2018 International Joint Conference on Neural Networks (IJCNN)*, Jul. 2018, pp. 1–8, doi: 10.1109/IJCNN.2018.8489399.

[9] G. Bathla, R. Rani, and H. Aggarwal, "Stocks of year 2020: prediction of high variations in stock prices using LSTM," *Multimed. Tools Appl.*, vol. 82, no. 7, pp. 9727–9743, Mar. 2023, doi: 10.1007/s11042-022-12390-5.

[10] A. N. . F. Faisal, A. Rahman, M. T. M. Habib, A. H. Siddique, M. Hasan, and M. M. Khan, "Neural networks based multivariate time series forecasting of solar radiation using meteorological data of different cities of Bangladesh," *Results Eng.*, vol. 13, p. 100365, Mar. 2022, doi: 10.1016/j.rineng.2022.100365.

[11] M. Yang and J. Wang, "Adaptability of Financial Time Series Prediction Based on BiLSTM," *Procedia Comput. Sci.*, vol. 199, pp. 18–25, 2022, doi: 10.1016/j.procs.2022.01.003.

[12] O. Ben Fredj, A. Mihoub, M. Krichen, O. Cheikhrouhou, and A. Derhab, "CyberSecurity Attack Prediction: A Deep Learning Approach," in *13th International Conference on Security of Information and Networks*, Nov. 2020, pp. 1–6, doi: 10.1145/3433174.3433614.

[13] T. A. Rashid, P. Fattah, and D. K. Awla, "Using Accuracy Measure for Improving the Training of LSTM with Metaheuristic Algorithms," *Procedia Comput. Sci.*, vol. 140, pp. 324–333, 2018, doi: 10.1016/j.procs.2018.10.307.

[14] N. Passalis, A. Tefas, J. Kanniainen, M. Gabbouj, and A. Iosifidis, "Deep Adaptive Input Normalization for Time Series Forecasting," *IEEE Trans. Neural Networks Learn. Syst.*, vol. 31, no. 9, pp. 3760–3765, Sep. 2020, doi: 10.1109/TNNLS.2019.2944933.

[15] J. Wang, G. Wen, S. Yang, and Y. Liu, "Remaining Useful Life Estimation in Prognostics Using Deep Bidirectional LSTM Neural Network," in *2018 Prognostics and System Health Management Conference (PHM-Chongqing)*, Oct. 2018, pp. 1037–1042, doi: 10.1109/PHM-Chongqing.2018.00184.

[16] A. P. Wibawa, W. Lestari, A. B. P. Utama, I. T. Saputra, and Z. N. Izdihar, "Multilayer Perceptron untuk Prediksi Sessions pada Sebuah Website Journal Elektronik," *Indones. J. Data Sci.*, vol. 1, no. 3, Dec. 2020, doi: 10.33096/ijodas.v1i3.15.

[17] A. P. Wibawa, Z. N. Izdihar, A. B. P. Utama, L. Hernandez, and Haviluddin, "Min-Max Backpropagation Neural Network to Forecast e-Journal Visitors," in *2021 International Conference on Artificial Intelligence in Information and Communication (ICAIIC)*, Apr. 2021, pp. 052–058, doi: 10.1109/ICAIIC51459.2021.9415197.

[18] A. P. Wibawa, "Mean-Median Smoothing Backpropagation Neural Network to Forecast Unique Visitors Time Series of Electronic Journal," *J. Appl. Data Sci.*, vol. 4, no. 3, pp. 163–174, Sep. 2023, doi: 10.47738/jads.v4i3.97.

[19] A. P. Wibawa, I. T. Saputra, A. B. P. Utama, W. Lestari, and Z. N. Izdihar, "Long Short-Term Memory to Predict Unique Visitors of an Electronic Journal," in *2020 6th International Conference on Science in Information Technology (ICSITech)*, Oct. 2020, pp. 176–179, doi: 10.1109/ICSITech49800.2020.9392031.

[20] A. P. Wibawa, R. R. Ula, A. B. P. Utama, M. Y. Chuttur, A. Pranolo, and Haviluddin, "Forecasting e-Journal Unique Visitors using Smoothed Long Short-Term Memory," in *2021 7th International Conference on Electrical, Electronics and Information Engineering (ICEEIE)*, Oct. 2021, pp. 609–613, doi: 10.1109/ICEEIE52663.2021.9616628.

[21] W. Y. Ayele, "Adapting CRISP-DM for Idea Mining," *Int. J. Adv. Comput. Sci. Appl.*, vol. 11, no. 6, 2020, doi: 10.14569/IJACSA.2020.0110603.

[22] H. Wiemer, L. Drowatzky, and S. Ihlenfeldt, "Data Mining Methodology for Engineering Applications (DMME)—A Holistic Extension to the CRISP-DM Model," *Appl. Sci.*, vol. 9, no. 12, p. 2407, Jun. 2019, doi: 10.3390/app9122407.

[23] C. Schröer, F. Kruse, and J. M. Gómez, "A systematic literature review on applying CRISP-DM process model," *Procedia Comput. Sci.*, vol. 181, no. 2019, pp. 526–534, 2021, doi: 10.1016/j.procs.2021.01.199.

[24] X. Xiao, J. Liu, D. Liu, Y. Tang, and F. Zhang, "Condition Monitoring of Wind Turbine Main Bearing Based on Multivariate Time Series Forecasting," *Energies*, vol. 15, no. 5, p. 1951, Mar. 2022, doi: 10.3390/en15051951.

[25] S. Bhanja and A. Das, "Deep Neural Network for Multivariate Time-Series Forecasting," 2021, pp. 267–277.

[26] S. Huber, H. Wiemer, D. Schneider, and S. Ihlenfeldt, "DMME: Data mining methodology for engineering applications – a holistic extension to the CRISP-DM model," *Procedia CIRP*, vol. 79, pp. 403–408, 2019, doi: 10.1016/j.procir.2019.02.106.

[27] T. Emmanuel, T. Maupong, D. Mpoeleng, T. Semong, B. Mphago, and O. Tabona, "A survey on missing data in machine learning," *J. Big Data*, vol. 8, no. 1, p. 140, Oct. 2021, doi: 10.1186/s40537-021-00516-9.

[28] A. Mirzaei, S. R. Carter, A. E. Patanwala, and C. R. Schneider, "Missing data in surveys: Key concepts, approaches, and applications," *Res. Soc. Adm. Pharm.*, vol. 18, no. 2, pp. 2308–2316, Feb. 2022, doi: 10.1016/j.sapharm.2021.03.009.

[29] P. J. Muhammad Ali, "Investigating the Impact of Min-Max Data Normalization on the Regression Performance of K-Nearest Neighbor with Different Similarity Measurements," *Aro-the Sci. J. Koya Univ.*, vol. 10, no. 1, pp. 85–91, 2022, doi: 10.14500/aro.10955.

[30] H. Henderi, "Comparison of Min-Max normalization and Z-Score Normalization in the K-nearest neighbor (kNN) Algorithm to Test the Accuracy of Types of Breast Cancer," *IJIIS Int. J. Informatics Inf. Syst.*, vol. 4, no. 1, pp. 13–20, 2021, doi: 10.47738/ijiis.v4i1.73.

[31] A. J. Mohammed, "Improving Classification Performance for a Novel Imbalanced Medical Dataset using SMOTE Method," *Int. J. Adv. Trends Comput. Sci. Eng.*, vol. 9, no. 3, pp. 3161–3172, Jun. 2020, doi: 10.30534/ijatcse/2020/104932020.

[32] S. F. M. Radzi, M. K. A. Karim, M. I. Saripan, M. A. A. Rahman, I. N. C. Isa, and M. J. Ibahim, "Hyperparameter tuning and pipeline optimization via grid search method and tree-based autoML in breast cancer prediction," *J. Pers. Med.*, vol. 11, no. 10, 2021, doi: 10.3390/jpm11100978.

[33] B. H. Shekar and G. Dagnew, "Grid Search-Based Hyperparameter Tuning and Classification of Microarray Cancer Data," in *2019 Second International Conference on Advanced Computational and Communication Paradigms (ICACCP)*, Feb. 2019, pp. 1–8, doi: 10.1109/ICACCP.2019.8882943.

[34] A. Pranolo, Y. Mao, A. P. Wibawa, A. B. P. Utama, and F. A. Dwiyanto, "Robust LSTM With Tuned-PSO and Bifold-Attention Mechanism for Analyzing Multivariate Time-Series," *IEEE Access*, vol. 10, pp. 78423–78434, 2022, doi: 10.1109/ACCESS.2022.3193643.

[35] W. Elmasry, A. Akbulut, and A. H. Zaim, “Evolving deep learning architectures for network intrusion detection using a double PSO metaheuristic,” *Comput. Networks*, vol. 168, p. 107042, Feb. 2020, doi: 10.1016/j.comnet.2019.107042.

[36] W. Sun and C. Huang, “A novel carbon price prediction model combines the secondary decomposition algorithm and the long short-term memory network,” *Energy*, vol. 207, p. 118294, Sep. 2020, doi: 10.1016/j.energy.2020.118294.

[37] W. M. Ridwan, M. Sapitang, A. Aziz, K. F. Kushiar, A. N. Ahmed, and A. El-Shafie, “Rainfall forecasting model using machine learning methods: Case study Terengganu, Malaysia,” *Ain Shams Eng. J.*, vol. 12, no. 2, pp. 1651–1663, Jun. 2021, doi: 10.1016/j.asej.2020.09.011.

[38] T. B. Pun and T. B. Shahi, “Nepal Stock Exchange Prediction Using Support Vector Regression and Neural Networks,” *Proc. 2018 2nd Int. Conf. Adv. Electron. Comput. Commun. ICAECC 2018*, pp. 1–6, 2018, doi: 10.1109/ICAECC.2018.8479456.

[39] Z. Lyu *et al.*, *Neuroevolution of recurrent neural networks for time series forecasting of coal-fired power plant operating parameters*, vol. 1, no. 1. Association for Computing Machinery, 2021.