A Web-Based Machine Learning Approach for Standardized Precipitation Index Prediction

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ABSTRACT
Accurate and user-friendly drought forecasting tools are crucial for mitigating the impact of meteorological droughts, particularly in vulnerable areas such as South Sumatra, Indonesia. This study introduces an interactive web-based application built to anticipate drought conditions by forecasting the Standardized Precipitation Index (SPI). The system relies on deep learning techniques trained using three decades of rainfall data collected from the Climatological Station in South Sumatra. In evaluating model performance, both Recurrent Neural Network (RNN) and Long Short-Term Memory (LSTM) architectures were assessed. While both models delivered comparable short-term predictions, the LSTM experienced a significant decline in accuracy over extended forecasting periods (specifically at SPI-6), primarily due to overfitting. In contrast, the RNN displayed more stable and reliable results, making it the preferable model for this geographical context. Specifically, the RNN achieved a lower Mean Absolute Error (MAE) of 0.4007, a reduced Root Mean Squared Error (RMSE) of 0.4684, and a higher coefficient of determination (R^2) of 0.7338. These metrics outperformed those of the LSTM, which recorded a MAE of 0.4115, an RMSE of 0.4840, and an R^2 of 0.7036. Such results confirm that the RNN offers a more precise and dependable fit for the station's dataset. The web platform also effectively visualizes the model outputs, providing a dynamic and interactive 24-month forecast view that supports early warning efforts and informed decision-making for regional authorities and stakeholders.

Keyword: web-based prediction, machine learning, Standardized Precipitation Index, drought

1. INTRODUCTION

The Standardized Precipitation Index (SPI) is a commonly adopted tool for assessing drought conditions. Derived from precipitation records, SPI offers a numerical representation of either dry or moist climatic conditions in a given area. This index was specifically developed to characterize and track drought events over various temporal scales using long-term rainfall data. Beyond its utility in identifying dry periods, SPI also serves as an indicator of unusual wet conditions. It can be applied across a range of time intervals, such as 1, 3, 6, 9, 12, and up to 72 months, making it an effective metric for understanding regional drought patterns over both short and extended durations [1]. Precipitation refers to the process by which water vapor in the atmosphere condenses and descends to the Earth's surface, either in liquid or solid form. This includes various types such as rain, drizzle, snow, hail, ice pellets, snowflakes, or even ice crystals that may fall from clear skies as fine particles. The total volume of precipitation over a specified time frame is typically measured as the vertical depth of water (or its solid equivalent) that would uniformly coat a flat area of the Earth's surface [2].

Monitoring and interpreting weather patterns play a vital role in enhancing community readiness against the adverse effects brought about by climate fluctuations. Among the various weather-related hazards, drought stands out as a slow-onset disaster marked by an extended period of minimal rainfall, eventually resulting in severe water scarcity. This condition is typically associated with depleted soil moisture and insufficient water availability for crops due to persistent dryness. Drought has consistently been linked to substantial damage, with the agricultural sector bearing the brunt of its impacts. Prolonged dry periods also elevate the risk of wildfires, compounding ecological degradation [3]. In Indonesia, particularly in regions like South Sumatra, drought is a recurrent hydrometeorological challenge, significantly disrupting farming, water supply systems, and local economies. Data from the Meteorology, Climatology, and Geophysics Agency (BMKG) revealed that South Sumatra faced its driest spell in August 2024, enduring a stretch of 60 days without rain.

The emergence of advanced machine learning techniques, especially deep learning models such as Recurrent Neural Networks (RNNs) and their extension, Long Short-Term Memory (LSTM), has significantly enhanced the capability to analyze time-series datasets, including historical precipitation records. These models excel at capturing intricate temporal relationships that traditional statistical approaches often fail to detect, making them particularly effective for forecasting the Standardized Precipitation Index (SPI). In a study conducted in Mexico, Magallanes-Quintanar et al. [4] applied the LSTM model for SPI prediction. Their findings demonstrated that LSTM could effectively learn temporal dynamics; however, a more recent approach—Neural Hierarchical Interpolation for Time Series Forecasting (N-HiTS)—outperformed LSTM in terms of key performance indicators like Mean Squared Error (MSE) and the coefficient of determination (R^2). While the LSTM model remains a strong and dependable option, the study emphasizes areas where it can be further optimized. Furthermore, the research underscores the relevance of applying machine learning-driven approaches for time series prediction in drought assessment. A comprehensive review by Z. Liu et al. [5] categorized various machine learning and deep learning strategies for forecasting time-dependent data. Within this framework, LSTM is highlighted as particularly well-suited for capturing long-range dependencies in complex sequences, such as those found in SPI datasets that exhibit both seasonal variability and extended trends influenced by rainfall patterns.

Although predictive models such as RNN and LSTM offer strong analytical capabilities, their impact becomes significantly more meaningful when the results are presented in a format that is both accessible and interpretable for relevant stakeholders. Delivering these insights through a web-based interface emerges as an effective approach to simplify and communicate complex climatological data interactively. This study outlines the creation of a web application tailored to forecast and display the Standardized Precipitation Index (SPI) for the South Sumatra Climatological Station, a critical monitoring site located in Palembang. The main goals of this research include: developing and evaluating RNN and LSTM architectures for predicting SPI at various time scales (SPI-1, SPI-3, and SPI-6) using long-term precipitation records from the station; producing reliable SPI forecasts to assess potential drought risks in the Palembang area; and designing a user-friendly, online visualization platform to present these forecasts. By integrating advanced modeling with accessible technology, this work seeks to offer a practical tool that enhances climate data interpretation and supports informed decision-making in regional drought management efforts.

2. METHODOLOGY

This study adopts a structured and methodical research framework. The flowchart presented in the design provides detailed insight into each phase of the research process. It outlines the sequential steps from initial data preparation to the final deployment of the trained model. The workflow begins with the acquisition of historical rainfall data, followed by preprocessing and the calculation of the Standardized Precipitation Index (SPI). It then proceeds to the construction and training of both RNN and LSTM models, concluding with model testing and validation. The SPI prediction framework is designed to produce accurate drought forecasts. The ultimate outcome of this process is the generation and visualization of SPI-1, SPI-3, and SPI-6 predictions for the years 2025 and 2026, utilizing the superior-performing model between the two. In essence, the algorithm operates by receiving input data, initializing and configuring the prediction model, executing the forecasting process, and finally categorizing the SPI results.

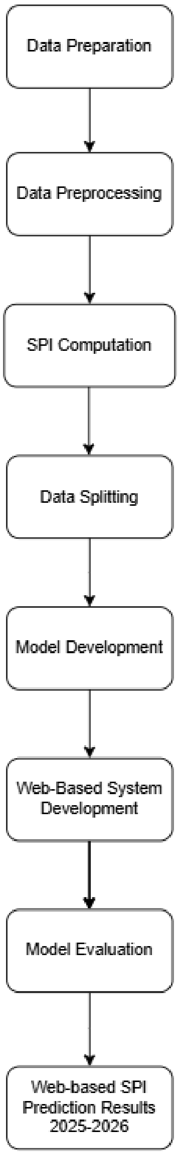

Figure 1. Research Flowchart

A. Data Preparation

This study was conducted using data from the South Sumatra Climatological Station, an essential meteorological monitoring site located in Palembang, South Sumatra. The dataset comprised daily rainfall records collected over a 30-year timeframe, starting from January 1, 1993, through December 31, 2024. These records were retrieved via BMKGSoft, an internal data management system operated by the Meteorology, Climatology, and Geophysics Agency (BMKG). Within the BMKGSoft platform, the station is referenced under the name 'Staklim Palembang'. Prior to conducting further analysis, a preprocessing stage was carried out to refine the dataset, this included cleaning procedures to uphold data integrity and addressing issues such as missing or invalid entries.

B. Data Preprocessing

Prior to training the model, the raw daily rainfall data was subjected to a thorough preprocessing phase to maintain its reliability and usability. Within the dataset, any instances of the values 8888 and 9999 were standardized by converting them to 0, a format recognized by most data processing libraries. To convert the data into a usable form for the SPI calculation, the daily rainfall measurements were compiled into monthly totals. This aggregation was accomplished using the Pandas library in Python, which facilitated efficient data transformation and handling.

C. Standardized Precipitation Index Computation

The Standardized Precipitation Index (SPI) is a statistical tool developed to quantify deviations in precipitation across multiple timeframes. First introduced by McKee in 1993, this metric was designed to aid in identifying drought episodes as well as monitoring general climate fluctuations [3]. To enhance the interpretation of hydrological anomalies, Global Modelling and Assimilation Office (GMAO) offers a standardized classification scheme for SPI scores, which enables users to gauge the severity of both dry and wet conditions based on the computed index values.

Table 1. SPI Classification

Precipitation Regime	SPI Values
Extremely wet	>2.0
Very wet	1,5 to 1,99
Moderately wet	1 to 1,49
Normal	-0,99 to 0,99
Moderately dry	-1,49 to -1
Very dry	-1,99 to -1,5
Extremely dry	≤ -2.0

Based on the aggregated monthly precipitation data, the Standardized Precipitation Index (SPI) was computed at different temporal resolutions, specifically for one-month (SPI-1), three-month (SPI-3), and six-month (SPI-6) intervals. To derive these values, the accumulated rainfall figures were initially modeled using a Gamma probability distribution. Following this, a transformation into a standard normal distribution was performed, resulting in the final SPI values for each respective timescale. Figure 2 below shows the calculated historical SPI values for the station.

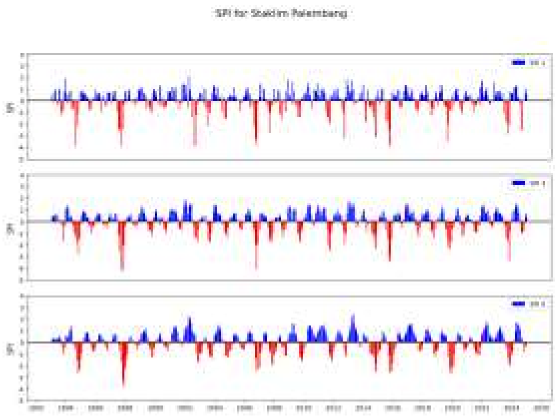

Figure 2. Historical SPI-1, SPI-3, and SPI-6 time-series (1993-2024). Red bars indicate dry periods (negative SPI) and blue bars indicate wet periods (positive SPI).

The average SPI values for the analyzed period are close to zero, specifically, 0.020 for SPI-1, 0.012 for SPI-3, and 0.002 for SPI-6, indicating that, overall, rainfall conditions at South Sumatra Climatological Station were generally stable or neutral. To offer further insight, the lowest recorded SPI values reflect pronounced dry episodes, with minimums of -3.888 for SPI-1, -4.216 for SPI-3, and -3.748 for SPI-6. Conversely, the maximum

SPI values suggest periods of substantial wetness, with corresponding peaks of 2.138, 1.819, and 2.395, respectively, further reinforcing the variability in precipitation extremes during the observed timeframe.

D. Data Splitting

In this study, a lag value of 12 was selected due to the inherently seasonal nature of climate data, which often exhibits recurring annual patterns over a 12-month cycle. The dataset was divided into two segments: the training set, comprising records from January 1994 through December 2023 (with data from January to December 1993 excluded after applying the lag), and the testing set, which includes data from January to December 2024. The testing set represents previously unseen data, allowing the model's predictive capability to be objectively evaluated. Prior to being processed by the predictive models, both the training and testing datasets were scaled using the MinMaxScaler method provided by the scikit-learn library to ensure consistent normalization.

E. Model Development

The process of model construction commenced with the importation of several foundational Python libraries, including Pandas, NumPy, Matplotlib, SciPy, Scikit-learn, TensorFlow, and Keras. Both the RNN and LSTM models were structured with four successive LSTM layers containing 128, 64, 32, and 16 units, respectively. To enhance model generalization and stabilize the training process, each layer integrated L2 regularization, a dropout mechanism set at 0.3, and batch normalization. The final stage of the architecture included a single Dense layer to produce the output predictions. Model compilation utilized the Adam optimizer, paired with a learning rate of 0.001 and the mean squared error (MSE) as the loss function. Adam was selected due to its adaptive learning capabilities, fast convergence behavior, and reliability in handling complex, non-linear, and non-stationary time-series data such as those encountered in climate forecasting [6]. The training process was configured to run for up to 300 epochs using a batch size of 16. An EarlyStopping callback was implemented, which halted training when no further improvement in validation loss was detected over 20 consecutive epochs. This validation was specifically monitored using the 2024 test dataset to ensure optimal model performance.

F. Web-Based System Development

To present the forecasting output in a user-friendly and interactive manner, a web-based Graphical User Interface (GUI) was implemented. This interface was designed to display various components, including past rainfall records, model performance metrics, and projections of future SPI values. The visual layout and user interaction elements were developed using HTML for the front-end. Meanwhile, the application's functionality and data processing were likely managed through a server-side scripting language such as PHP, which is widely utilized in creating dynamic web platforms.

3. RESULTS AND DISCUSSION

A. Model Evaluation

To evaluate the effectiveness of the trained models, three well-established statistical indicators were employed: Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and the Coefficient of Determination (R^2). These metrics together provide a robust framework for assessing the accuracy and dependability of the model outputs.

RMSE quantifies the average magnitude of prediction errors by calculating the square root of the mean squared differences between predicted and actual values. A lower RMSE value, ideally nearing zero, reflects higher predictive precision. This metric has become a cornerstone in the evaluation of models across meteorology, air quality studies, and climate simulations [7].

MAE represents the mean of the absolute differences between forecasted and observed values. It provides a clear and intuitive understanding of model accuracy, with lower MAE scores indicating improved prediction performance. MAE is extensively used as a fundamental benchmark in model validation. Although RMSE and MAE are both widely adopted for error evaluation, consensus on the most optimal metric for assessing forecasting error remains unresolved [7].

R^2, also known as the Coefficient of Determination, reflects the proportion of variability in the dependent variable that can be accounted for by the independent variables involved in the model [8].

The predictive capabilities of both RNN and LSTM models were tested using data from the South Sumatra Climatological Station. A narrative interpretation accompanies the numerical findings presented in Table 2 and the subsequent figures, which illustrate the model accuracy and project future SPI values.

Table 2. Model Evaluation

Location	Model	SPI	MAE	RMSE	R^2
Staklim Palembang	LSTM	SPI-1	0.413297	0.540356	0.711748
Staklim Palembang	LSTM	SPI-3	0.300243	0.339870	0.839748
Staklim Palembang	LSTM	SPI-6	0.520977	0.571826	0.559396
Staklim Palembang	RNN	SPI-1	0.488053	0.555740	0.695101
Staklim Palembang	RNN	SPI-3	0.346611	0.416463	0.759381
Staklim Palembang	RNN	SPI-6	0.367493	0.433182	0.747151

The detailed metrics are presented in Table 2 above. The LSTM model demonstrated superior performance for short and medium-term predictions (SPI-1 and SPI-3), while the RNN model was surprisingly more effective for the longer-term SPI-6 forecast.

When predicting SPI-1 values, the LSTM model demonstrated slightly superior performance, achieving an R^2 score of 0.7117, compared to the RNN model’s 0.6951. The performance gap widened noticeably in the SPI-3 forecast, where LSTM attained an impressive R^2 of 0.8397, highlighting its strong capability for capturing medium-range seasonal precipitation variability. Interestingly, this trend reversed in the SPI-6 prediction results. In this longer-term forecast, the RNN model produced a substantially higher R^2 of 0.7472, outperforming the LSTM’s 0.5594. This unexpected outcome indicates that the RNN's simpler network structure may have been better suited to identifying and generalizing the more stable and gradual trends characteristic of long-term SPI data. Meanwhile, the LSTM’s increased complexity might have led to overfitting, reducing its predictive accuracy for SPI-6 in this specific context.

Table 3. Comparison of Average Evaluation Metrics

Model	MAE	RMSE	R^2
LSTM	0.411505	0.371847	0.703631
RNN	0.400719	0.484017	0.733878

A key finding from the model evaluation is the performance reversal on the SPI-6 prediction scale. In contrast to its superior performance on other scales, the LSTM model's accuracy dropped significantly for SPI-6. This drastic decrease indicates that the more complex LSTM architecture was indicated prone to overfitting when modeling the smoother long-term trend data at this location, whereas the simpler RNN model was able to generalize more effectively. Due to this significant drop in LSTM's long-term performance, the overall average performance of the RNN model is considered more reliable and robust for South Sumatra Climatological Station.

The visualization of the 2024 actual versus predicted test data shown in Figure 3 below.

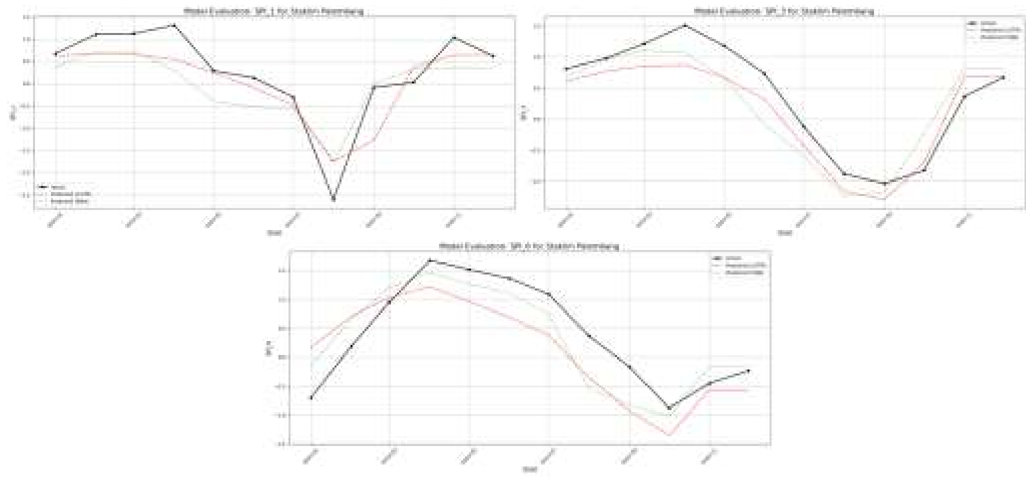

Figure 3. SPI Actual vs. Predicted

B. Web Interface and Prediction

A web-based interface system was developed to present research results in an interactive and easily accessible manner. The Graphical User Interface (GUI) has a structured layout, consisting of a navigation panel on the left side and a main content area on the right side that displays various data visualizations and research information. The vertical navigation panel on the left provides quick access to the main pages of the site:

- Home Tab: the main and initial page.
- About Tab: contains a brief description of the Standardized Precipitation Index (SPI) as well as the background and objectives of the research project.
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Figure 4. Home and About Tab

- SPI Historical Data Tab: contains information on the classification of Standardized Precipitation Index (SPI) values and displays a focused graph of historical SPI calculation results. In the SPI value classification, a static table is presented detailing weather condition classifications based on SPI value ranges, covering categories from “Extremely Dry” (value ≤ -2.0) to “Extremely Wet” (value ≥ 2.0) to assist users in interpreting the results. The visualization displays historical SPI data in the form of an interactive bar chart. Users can select the station location, SPI scale (SPI-1, SPI-3, SPI-6), and time range. Blue bars represent positive SPI values (wet conditions), while red bars represent negative SPI values (dry conditions).

Figure 5. SPI Historical Data Tab

- Model Evaluation Tab: a key element for showing the performance comparison between the deep learning models used. This line graph compares actual data with prediction results from two different models:
  a. Actual Data: represented by the black line, showing the actual SPI values recorded from observational data calculations.
  b. LSTM Prediction: represented by the red line, showing prediction results using the Long Short-Term Memory model.
  c. RNN Prediction: represented by the green line, showing the predicted results using the Recurrent Neural Network model.

Figure 6. Model Evaluation Tab

- SPI Prediction Tab: displays the SPI prediction results for the years 2025 and 2026. Users can select the type of SPI to view the monthly condition projections for the 2025-2026 period. The graph is accompanied by threshold line labels such as “Moderately Dry,” “Very Dry,” and “Extremely Dry,” making it easier for users to visually identify potential drought risks.

Figure 7. SPI Prediction Tab – Predicted SPI-1

Figure 8. Predicted SPI-3

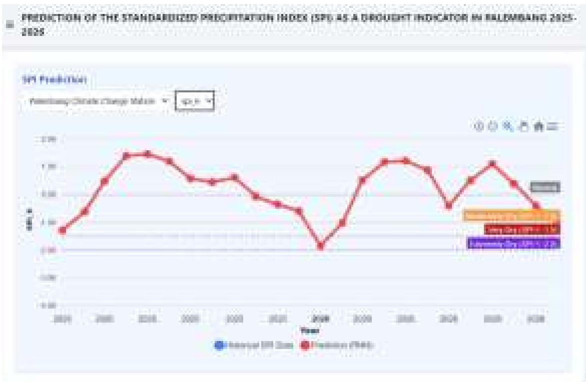

Figure 9. Predicted SPI-6

The forecast outcomes for the South Sumatra Climatological Station (Staklim Palembang) reveal a steady and pronounced indication of increasingly dry conditions across short-, medium-, and longer-term timescales. According to the LSTM model, SPI-1 is projected to decline from a near-neutral mean of 0.001 in 2025 to -0.066 by 2026. This downward trend becomes more apparent over the 3-month interval, where the SPI-3 average drops from 0.179 in 2025 to 0.066 in 2026 under the same model. The most dramatic shift, however, is observed in the SPI-6 forecast: the RNN model anticipates a sharp reduction, with values falling from 0.270 in 2025 to 0.096 in 2026. Such consistent downward movement across different temporal resolutions highlights a growing susceptibility of the region to hydrological stress and the looming threat of drought in 2026.

- Research Location Map Tab: located at the bottom of the page, a map showing the geographical location of South Sumatra Climatological Station.

Figure 10. Research Location Map Tab

4. CONCLUSIONS

Through the integration of deep learning techniques, this study effectively applied both Recurrent Neural Network (RNN) and Long Short-Term Memory (LSTM) models to forecast the Standardized Precipitation Index (SPI), with the results deployed via a dynamic, web-based platform. The LSTM model demonstrated stronger predictive accuracy for short- and medium-term intervals—specifically SPI-1 and SPI-3—while the RNN model delivered better results when forecasting long-term trends such as SPI-6 in the South Sumatra Climatological Station area. On average, the RNN model outperformed its counterpart, as evidenced by its lower error values (MAE: 0.4007 and RMSE: 0.4684) and a superior R^2 score of 0.7338, suggesting a more accurate and reliable performance that aligns more closely with the station's climatic characteristics. The RNN's less complex structure enabled it to maintain stability and avoid overfitting, a challenge that adversely affected the LSTM model's ability to generalize long-range patterns—particularly for SPI-6—thus tipping the overall performance comparison in favor of RNN. Forecast outcomes from the model point to a steadily intensifying drying pattern between 2025 and 2026 for the region, signaling a heightened vulnerability to drought conditions and underlining the need for proactive response by local decision-makers. The developed web interface effectively presents these SPI projections, offering an intuitive and accessible platform for stakeholders to monitor and interpret drought risk throughout the forecast period.

ACKNOWLEDGEMENT

The authors wish to acknowledge the invaluable contributions that made this research possible. Our sincere appreciation also goes to the State College of Meteorology, Climatology, and Geophysics (STMKG) for their continuous academic mentorship, institutional backing, and provision of essential research facilities that facilitated the completion of this work.

REFERENCES

[1] M. N. Lorenzo, H. Pereira, I. Alvarez, and J. M. Dias, "Standardized Precipitation Index (SPI) evolution over the Iberian Peninsula during the 21st century," *Atmos. Res.*, vol. 297, no. February 2023, 2024, doi: 10.1016/j.atmosres.2023.107132.

[2] WMO, *Guide to Instruments and Methods of Observation*, vol. V, no. 8. 2023.

[3] C. Liu, C. Yang, Q. Yang, and J. Wang, "Spatiotemporal drought analysis by the standardized precipitation index (SPI) and standardized precipitation evapotranspiration index (SPEI) in Sichuan Province, China," *Sci. Rep.*, vol. 11, no. 1, pp. 1-14, 2021, doi: 10.1038/s41598-020-80527-3.

[4] R. Magallanes-Quintanar, C. E. Galván-Tejada, J. I. Galván-Tejada, H. Gamboa-Rosales, S. de J. Méndez-Gallegos, and A. García-Domínguez, "Neural Hierarchical Interpolation for Standardized Precipitation Index Forecasting," *Atmosphere (Basel).*, vol. 15, no. 8, 2024, doi: 10.3390/atmos15080912.

[5] Z. Liu, Z. Zhu, J. Gao, and C. Xu, "Forecast Methods for Time Series Data: A Survey," *IEEE Access*, vol. 9, pp. 91896-91912, 2021, doi: 10.1109/ACCESS.2021.3091162.

[6] J. Wang, Y. Zou, and S. J. Lim, "An Improved Time Feedforward Connections Recurrent Neural Networks," *Intell. Autom. Soft Comput.*, vol. 36, no. 3, pp. 2743-2755, 2023, doi: 10.32604/iasc.2023.033869.

[7] T. O. Hodson, "Root-mean-square error (RMSE) or mean absolute error (MAE): when to use them or not," *Geosci. Model Dev.*, vol. 15, no. 14, pp. 5481-5487, 2022, doi: 10.5194/gmd-15-5481-2022.

[8] A. V Tatachar, "Comparative assessment of regression models based On model evaluation metrics," *Int. Res. J. Eng. Technol.*, vol. 8, no. 9, pp. 853-860, 2021, [Online]. Available: https://d1wqtxts1xzle7.cloudfront.net/73250877/IRJET_V8I9127-libre.pdf